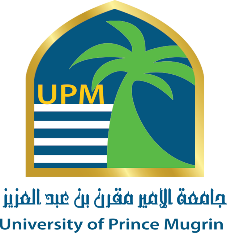
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**Project Report**

**Bitcoin Price Predictor**

**Data Mining – AI306**

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# Abstract

* Brief overview of the study’s objective: predicting Bitcoin prices
* Summary of methodology: data sources, models used
* Key findings and implications

# Introduction

Bitcoin, the world’s leading cryptocurrency since around 2013, is known for its high volatility and unpredictable price movements. Therefore, accurate price prediction is crucial for traders and investors aiming to navigate this dynamic market and actually be successful in it. Traditional statistical methods often fall short in capturing Bitcoin’s complex behaviour, while machine learning and deep learning models offer new potential for better and more accurate forecasts. This study compares several predictive approaches using historical Bitcoin data to identify effective strategies for price prediction and support informed decision-making in the cryptocurrency market.

# Literature Review (Related Work)

Recent research on Bitcoin price prediction and broader sequence modeling has explored a wide range of machine learning and deep learning approaches aimed at improving forecasting accuracy and efficiency. Mohammadjafari (2024) compared Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models using historical Bitcoin price data, demonstrating that GRUs outperformed LSTMs by achieving a lower mean squared error (MSE) and faster training times. The study highlighted GRUs as more computationally efficient while maintaining the ability to capture long-term dependencies, making them well-suited for financial time series forecasting.

Swetha (2022) extended the comparison of predictive models by evaluating traditional machine learning models, such as Linear Regression and Facebook Prophet, alongside LSTM networks for Bitcoin, Ethereum, and Litecoin price forecasting. The results indicated that while Linear Regression achieved high R² values, LSTM models delivered lower root mean squared error (RMSE) values, demonstrating superior generalization to unseen data. The study emphasized the necessity of including broader features beyond closing prices for enhanced prediction robustness.

Building on the limitations of recurrent architectures, Khaniki and Manthouri (2024) introduced a hybrid model combining the Performer—a scalable Transformer variant— with Bidirectional LSTM (BiLSTM) networks and technical indicators such as RSI, SMA, and Bollinger Bands. Their Transformer-enhanced model achieved the lowest RMSE and highest R² across Bitcoin, Ethereum, and Litecoin datasets on both daily and hourly scales. This work illustrated the significant potential of integrating attention mechanisms and feature engineering for improving cryptocurrency price prediction.

In parallel, Udom (2019) investigated Bitcoin return prediction through a hybrid ARIMAGARCH approach, modeling both the mean and volatility of Bitcoin daily returns. The study found that an ARIMA(2,0,1)-GARCH(1,1) model with a Normal error distribution provided the most accurate forecasts. This highlights the importance of capturing both the time series' autocorrelation and volatility characteristics, reinforcing the value of statistical hybrid models in financial forecasting tasks.

Beyond Bitcoin-specific forecasting, Bai, Kolter, and Koltun (2018) challenged the traditional dominance of recurrent networks in sequence modeling by systematically evaluating generic recurrent networks (LSTM, GRU) against a simple Temporal Convolutional Network (TCN). Their empirical results showed that TCNs consistently outperformed recurrent models across synthetic and real-world sequence modeling benchmarks, offering better long-term memory retention, parallelism, and training stability. This study suggests that convolutional architectures, such as TCNs, should be regarded as a powerful and potentially superior alternative to recurrent models for sequence-based financial prediction tasks, including Bitcoin price forecasting.

Expanding the broader context of time series modeling, the MOMENT framework addressed critical limitations in developing foundation models for time series analysis. Unlike domains such as NLP and vision, time series datasets are fragmented and highly diverse, hindering pre-training at scale. MOMENT introduced the Time Series Pile dataset and demonstrated that large-scale, multi-dataset pre-training significantly improves model generalization across diverse tasks under limited supervision. Their findings showed that time series-specific pre-trained models outperform adaptations of large language models, particularly in zero-shot and few-shot scenarios. Nevertheless, the study identified ongoing challenges regarding the full benefits of multi-dataset pretraining and robust performance in low-supervision settings, emphasizing important directions for future research.

Collectively, these studies reveal a progression from traditional statistical models to advanced deep learning and foundation model architectures, emphasizing the evolving understanding of memory, volatility, feature integration, attention mechanisms, and large-scale pre-training in enhancing Bitcoin price prediction and broader time series forecasting.

# Experiments

## a- Data Description

The dataset used in this study consists of historical Bitcoin price and trading data spanning from January 1, 2012, to January 1, 2025, totalling around 7 million entries. The data is organized in a time series format with a one-minute frequency, providing a comprehensive view of Bitcoin’s market activity over more than a decade.

Each record in the dataset includes the following features:

* **Timestamp**: Unix timestamp representing the precise minute of the record.
* **Open**: The price of Bitcoin at the start of the minute.
* **High**: The highest price reached within the minute.
* **Low**: The lowest price reached within the minute.
* **Close**: The price of Bitcoin at the end of the minute.
* **Volume**: The amount of Bitcoin traded during the minute.
* **Datetime**: Date and time corresponding to the timestamp (in YYYY-MM-DD Time:TImezone format)

A sample from the dataset is shown below:

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Timestamp | Open | High | Low | Close | Volume | Datetime |
| 1360887300.0 | 26.63 | 26.63 | 26.63 | 26.63 | 17.98955015 | 2013-02-15 00:15:00+00:00 |
| 1360887360.0 | 26.63 | 26.63 | 26.63 | 26.63 | 0.0 | 2013-02-15 00:16:00+00:00 |
| 1360887420.0 | 26.60 | 26.60 | 26.60 | 26.60 | 20.0 | 2013-02-15 00:17:00+00:00 |

This granular dataset enables detailed analysis and modelling of Bitcoin’s price dynamics, capturing both short-term fluctuations and long-term trends. The inclusion of open, high, low, close, and volume data supports the extraction of technical indicators and the development of robust predictive models.

## b- Data Preprocessing

* Handling missing values and outliers
* Feature engineering (e.g., lag features, moving averages)
* Data normalization or scaling
* Splitting data into training and test sets

## c- Models Built

* Description of baseline models (e.g., Linear Regression, ARIMA)
* Advanced models (e.g., Random Forest, LSTM, GRU)
* Hyperparameter tuning strategies

## d- Results

* Evaluation metrics (e.g., RMSE, MAE, R²)
* Comparative performance of models
* Visualization of predictions vs. actual prices

# Interpretation & Discussion

* Analysis of model performance
* Discussion of factors influencing prediction accuracy
* Limitations of the study
* Implications for traders and researchers

# Conclusion

* Recap of main findings
* Contributions to the field
* Suggestions for future work

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