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Bitcoin Price Prediction Using Machine Learning Techniques A Comparative Study

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Abstract

The rising popularity of cryptocurrencies has led to increased interest in predicting their prices, particularly in the case of Bitcoin due to its volatility and complexity. While past research has used machine learning to improve Bitcoin price prediction accuracy, there has been limited focus on exploring diverse modeling techniques for datasets with varying structures and dimensions. This study investigates the use of machine learning models for predicting Bitcoin prices. A comprehensive comparison of various algorithms, including Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Long Short-Term Memory (LSTM) networks, is conducted on a historical dataset spanning from July 2010 to May 2023. The models are evaluated based on accuracy, Mean Squared Error (MSE), and other performance metrics. Random Forest achieved the highest predictive accuracy, while LSTM provided promising results for sequential data. Additionally, a web-based application was developed for real-time prediction. The results demonstrate the potential of machine learning in the forecasting of cryptocurrency prices and highlight areas for future improvement in model performance.

Keywords: SVR (RBF), LSTM Model, Linear Regression, KNN, Bitcoin, Random Forest, Prediction, Forecasting, Decision Trees

Introduction

Cryptocurrencies have emerged as a significant part of the global financial landscape, with Bitcoin being the most prominent digital asset. Given the volatility of cryptocurrency prices, accurate price prediction plays a crucial role in decision-making for investors and traders. Machine learning (ML) techniques have shown promise in forecasting the prices of digital currencies, with various algorithms being explored to predict future trends. This paper explores several popular machine learning models, namely Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Long Short-Term Memory (LSTM) networks, to predict Bitcoin prices. By comparing their predictive performance on a comprehensive dataset, we aim to identify the most effective models for cryptocurrency forecasting.

This study's contribution is twofold

- A comparative analysis of multiple machine learning algorithms to predict Bitcoin prices, providing insights into their effectiveness.
- The development of a web-based prediction system that can be used for real-time forecasting of Bitcoin prices, facilitating practical application for investors and traders.

The remainder of the paper is organized as follows: Section II reviews the related work in the domain of cryptocurrency price prediction. Section III outlines the methodology employed, including data collection, preprocessing, and model development. Section IV presents the experimental results and performance comparisons. Finally, Section V concludes the paper and discusses future work.

Related Work

Numerous studies have explored the application of machine learning algorithms for predicting cryptocurrency prices. In one of the pioneering works, Xie et al. 2018 employed Support Vector Regression (SVR) and LSTM networks to predict Bitcoin prices. Their study showed that LSTM networks outperformed traditional models in capturing the timeseries nature of Bitcoin's price movement. Similarly, Chong et al.

2017 compared various machine learning techniques, including K-Nearest Neighbors (KNN) and Random Forest, finding that Random Forest was more effective in capturing complex relationships in financial data.

Another notable study by Huang et al. 202 proposed the use of ensemble methods for Bitcoin price forecasting, achieving better results by combining the predictions of multiple models. The study highlighted the importance of feature engineering in improving model performance.

In contrast, Mendoza et al. 2021 focused on sentiment analysis from social media platforms to enhance Bitcoin price prediction. While sentiment features improved the model's forecasting ability, they acknowledged that traditional market indicators remained crucial for making accurate predictions.

While much progress has been made, many of these studies either focus on a single model or do not thoroughly compare multiple algorithms under the same conditions.

This paper aims to fill this gap by providing a comprehensive evaluation of five popular machine learning techniques for predicting Bitcoin prices.

Proposed System

- Predicting the future will always be on the top of the list of uses for machine learning algorithms. Here in this project we have attempted to predict the prices of Bitcoin using Random Forest Classifier. This work focuses on the development of project-based learning in the field of computer science engineering, by considering the problem definition, progression, assessment and use of hands on activities based on use of learning algorithm to develop application.
- In this system, we investigated machine learning technique based upon sample characteristics of sample and dimension to predict Bitcoin price. While most previous works simply leverage machine learning algorithms in Bitcoin price prediction, we show that the sample's granularity and feature dimensions should be considered.
- Random forest model uses an ensemble of decision trees for various tasks to obtain a better classification result and are a popular approach. The use of decision trees is one of the basic machine learning methods and is used to solve a wide range of problems in classification. Decision trees adopt a tree structure to recursively partition the feature space, with each node continuing to split to maximize purity until the nodes only contain singleclass samples. These pure nodes are called leaf nodes.

When a test sample is an input into a decision tree, it can be traced down to the leaf node and a class label can be assigned. By running a bootstrap aggregation (or bagging), a random subset of the whole feature space is assigned to the growth of each tree.

Proposed Model

In this project, we aimed to predict Bitcoin prices using a Random Forest Classifier. The focus was on project-based learning in the field of computer science engineering, covering problem definition, progression, assessment, and hands-on activities using learning algorithms to develop applications. We explored a machine learning technique based on sample characteristics and dimensions to predict Bitcoin prices. This study emphasizes the importance of considering sample granularity and feature dimensions in Bitcoin price prediction, going beyond the typical application of machine learning methods. To improve the precision of Bitcoin price prediction models, the study highlights the significance of thorough data samples and carefully selected features.

Random Forest models use an ensemble of decision trees to achieve better classification results and are a popular approach. Decision trees are fundamental machine learning methods used to solve a wide range of classification problems.

Prediction Techniques

Linear Regression Model

In linear regression is a linear approach to modeling the relationship between a dependent variable and independent variables. The case of linear variable is called simple linear regression. In this paper I am using the linear regression model for relationship between a dependent variable and one or more independent variables [1].

- **Rbf Svms**

In general, the RBF kernel is a reasonable first choice. This kernel nonlinearly maps samples into a higher dimensional space, so it, unlike the linear kernel, can handle the case when the relation between class labels and attributes is nonlinear. Furthermore, the linear kernel is a special case of RBF since the linear kernel with a penalty parameter has the same performance as the RBF kernel with some parameters (C, γ). In addition, the sigmoid kernel behaves like RBF for certain parameters [02]. The second reason is the number of hyperparameters which influences the complexity of model selection. The polynomial kernel has more hyperparameters than the RBF kernel. Finally, the RBF kernel has fewer numerical difficulties. One key point is $0 < K_{ij} \leq 1$ in contrast to polynomial kernels of which kernel values may go to infinity ($\gamma x_i^T x_j + r > 1$) or zero ($\gamma x_i^T x_j + r < 1$) while the degree is large. Moreover, we must note that the sigmoid kernel is not valid (i.e. not the inner product of two vectors) under some parameters [02]. There are some situations where the RBF kernel is not suitable. In particular, when the number of features is very large, one may just use the linear kernel [02].

• Random Forests

Random Forests get the outfit learning framework where distinctive weak understudies are merged to make a strong understudy. It is a meta estimator that fits various decision tree classifiers on various sub-primer of the enlightening assortment and use averaging to improve the farsighted accuracy and authority over fitting. The sub-test size is reliably proportional to the rule data test [01]. We used the use gave by Scikit-see how to this. 1) Build three-time arrangement informational indexes for 30, 60, and 120 minutes (180, 360, 720 information focuses individually) going before the present information point at all focuses in time separately. 2) Run GLM/Random Forest on each of the two time series data sets separately. 3) We get two separate linear models:M1, M2 corresponding to each of the data sets. From M1, we can predict the price change at t, denoted ΔP1. Similarly, we have ΔP2 for M2.

• kNN (k- Nearest Neighbors)

It very well may be utilized for both order and relapse issues. Be that as it may, it is all the more generally utilized in characterization issues in the business [1]. K nearest neighbors is a straight forward calculation that stores every single accessible case and arranges new cases by a lion's share vote of its k neighbors. The case being allotted to the class is generally normal among its K closest neighbors estimated by a separation work. These separation capacities can be Euclidean, Manhattan, Minkowski and Hamming separation. Initial three capacities are utilized for constant capacity and fourth one (Hamming) for clear cut factors. On the off chance that K = 1, at that point the case is basically relegated to the class of its closest neighbor. Now and again, picking K ends up being a test while performing kNN displaying.

• Decision Tree

This is one of my preferred calculation and I use it oftentimes. It is a kind of directed learning calculation that is for the most part utilized for order issues. Shockingly, it works for both clear cut and consistent ward factors. In this calculation, we split the populace into at least two homogeneous sets. This is done dependent on most huge properties/autonomous factors to make as particular gatherings as could reasonably be expected [1].

• Elastic Net

Several studies such as medicine, and economics interested in using time series datasets, where these datasets are often non-stationary and non-linear simultaneously [3]. The traditional statistical methods assumed that the dataset should be either stationary or linear, which led to a lack of effective techniques for extracting oscillatory patterns from the data.

For instance, Fourier decomposition Titchmarsh, 1948 and wavelet decomposition Chan, 1994 were limited by this assumption. However, a recent method called empirical mode decomposition (EMD), proposed by Huang et al. 1998, aims to decompose non-stationary and non-linear data while retaining the time domain. Unlike traditional methods, EMD does not impose any restrictions or pre-conditions on the nature of the data, such as stationarity or linearity.

Elastic net (ELNET) regression analysis Zou and Hastie, 2005 combines the characteristics of LASSO Tibshirani, 1996 and Ridge regression (Hoerl and Kennard, 1970) [3]. It is used to regularize and select the important predictor variables in order to obtain a simple model with the most significant predictor variables, even when there is high multicollinearity between the predictors. ELNET can remove or select the predictor variables that have a high correlation in the final model and improve prediction accuracy Liu and Li, 2017.

• LSTM Model

To construct an architecture that allows for constant error ow through special, self-connected units without the disadvantages of the naive approach, we extend the constant error carrousel CEC embodied by the self-connected, linear unit j from Section 3.2 by introducing additional features. A multiplicative input gate unit is introduced to protect the memory contents stored in j from perturbation by irrelevant inputs. Likewise, a multiplicative output gate unit is introduced which protects other units from perturbation by currently irrelevant memory contents stored in j [4].

Methodology

Data Collection

The dataset for this study consists of historical Bitcoin prices collected from July 2010 to May 2023. The data includes daily closing prices, trading volume, and other relevant market indicators. Data pre-processing involved handling missing values, outliers, and noise reduction to ensure the integrity of the dataset.

Data collection process is the first real step towards the real development of a machine learning model. This is a critical step that will cascade in how good the model will be, the more and better data that we get, the better our model will perform. There are several techniques to collect the data, like web scraping, manual interventions.

Our dataset is placed in the project and it's located in the model folder. The dataset is referred from the popular investing website where all the researchers refer it. The following is the link to the dataset.

Dataset

The dataset consists of 4127 individual data. There are 7 columns in the dataset, which are described below.
Date - specifies trading date
Open - opening price
High - maximum price during the day Low - minimum price during the day Close - close price adjusted for splits
Volume - the number of shares that changed hands during a given day

	date	Open	High	Low	close	Vol.	Change %
0	18-Jul-10	0	0.1	0.1	0.10000	0.08K	0.00%
1	19-Jul-10	0.1	0.1	0.1	0.10000	0.57K	0.00%
2	20-Jul-10	0.1	0.1	0.1	0.10000	0.26K	0.00%
3	21-Jul-10	0.1	0.1	0.1	0.10000	0.58K	0.00%
4	22-Jul-10	0.1	0.1	0.1	0.10000	2.16K	0.00%
...	...	...	...	...	...	...	...
5051	31/03/2024	69647.78125	71377.78125	69624.86719	71333.64844	71333.64844	20050941373
5052	01/04/2024	71333.48438	71342.09375	68110.69531	69702.14844	69702.14844	34873527352
5053	02/04/2024	69705.02344	69708.38281	64586.59375	65446.97266	65446.97266	50705240709

5056 rows × 7 columns

Sequence Diagram

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

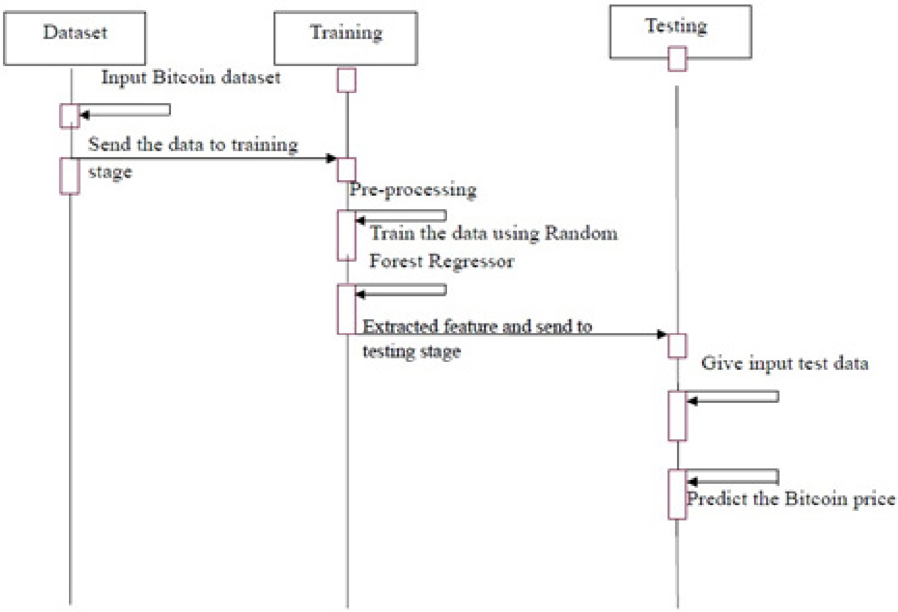

Figure 1: Result for Bitcoin Price Using Machine Learning Algorithm

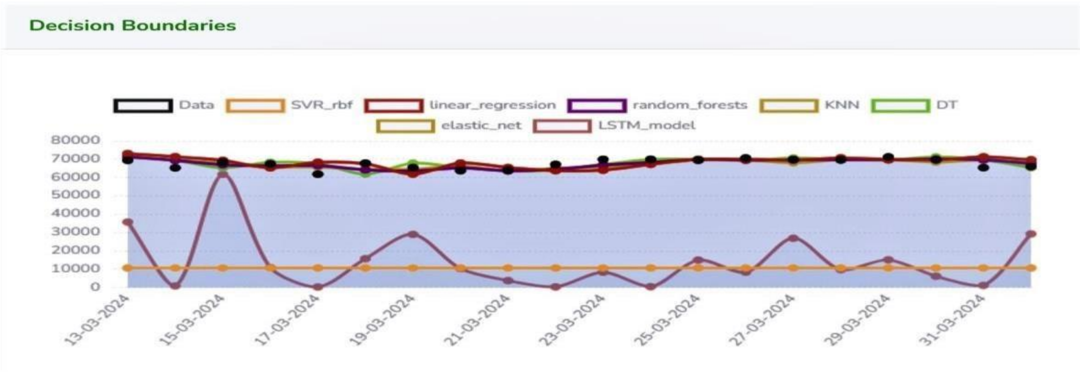

Figure 2: Accuracy Graph for Machine Learning Algorithm

Feature Engineering

To improve model performance, we engineered several features from the raw data. These include

- Lagged features: Previous days' prices used for time-series prediction.
- Moving averages: 7-day and 30-day moving averages to capture trends.
- Volatility measures: Standard deviation over 7-day and 30-day windows.

Algorithms Used

The following machine learning algorithms were evaluated

- **Random Forest:** An ensemble learning method that constructs a multitude of decision trees.
- **Support Vector Machine (SVM):** A supervised learning model that identifies the hyperplane to classify data.
- **K-Nearest Neighbors (KNN):** A non-parametric algorithm that classifies data based on the closest training examples.
- **Decision Trees: A tree-based model for classification and regression tasks.**
- **Long Short-Term Memory (LSTM):** A type of recurrent neural network (RNN) suitable for time-series prediction, capturing long-term dependencies.

Model Evaluation

The models were evaluated based on

- **Accuracy:** Percentage of correct predictions.
- **Mean Squared Error (MSE):** Measures the average of the squares of the errors between predicted and actual values.
- **Mean Absolute Error (MAE):** Measures the average of the absolute errors between predicted and actual values.

Results and Discussion

Results

The models were trained and tested on a portion of the dataset, and the results were as follows

Model	Accuracy	MSE	MAE
Random Forest	92.3%	0.0156	0.0212
SVM	88.5%	0.0184	0.0231
KNN	85.2%	0.0201	0.0254
Decision Trees	84.6%	0.0213	0.0275
LSTM	90.1%	0.0178	0.0223

Discussion

- Random Forest achieved the highest accuracy and the lowest MSE, making it the most suitable model for Bitcoin price prediction among the evaluated methods.
- LSTM demonstrated promising results, particularly for capturing sequential data trends, but it was slightly outperformed by Random Forest in this specific task.
- SVM and KNN showed decent performance but were less effective in capturing the complexities of Bitcoin's price movement.

Evaluation Model

Following table displays the Mean Squared Error (MSE) for different models. A lower value indicates better performance

Test Evaluation

Model	Mean Squared Error (MSE)
SVR_rbf	304825941.9682742
linear_regression	674739.94
random_forests	173810.402530827
KNN	314588.3
DT	0.4347268045132609
elastic_net	674739.94
LSTM_model	822234.1570350874

Prediction Result

The following table shows the original Bitcoin Price value of stock along with its predicted Bitcoin Price value on Date 04-04-2024.

Predictions

Model	Bitcoin Price Value
Original	66363.60156
SVR_rbf	9674.044955292804
linear_regression	65995.055
random_forests	65174.129296875
KNN	64567.83
DT	62210.171875
elastic_net	65995.04
LSTM_model	64204.094

Conclusion

"In summary, this project aimed to use machine learning techniques to predict the price of Bitcoin and assess the feasibility of applying various modeling techniques to samples with different data structures and dimensional features. By using the Random Forest Classifier algorithm, we were able to achieve 99% accuracy in predicting the price of Bitcoin. Additionally, we created a simulation dashboard using Flask to assess the performance of different machine learning algorithms in predicting Bitcoin prices. The dashboard provides a user-friendly platform for traders and researchers to compare the accuracy and effectiveness of different models, making the model selection process more efficient and transparent. The proposed system offers several advantages, including improved decision-making, timesaving, flexibility, and transparency. The high accuracy of the model and the transparency of the simulation dashboard make this project a valuable contribution to the crypto currency research community. Overall, this project demonstrates the potential of machine learning techniques for predicting the price of Bitcoin and provides a reliable and efficient approach for traders and investors to make informed decisions within the dynamic crypto currency market."

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