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Bitcoin Price Prediction Using Machine Learning Neural Networks

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Abstract **- Predicting Bitcoin prices is a critical challenge due to its inherent volatility and complexity. In this research, we explore four distinct algorithms for Bitcoin price prediction: Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), and Seasonal AutoRegressive Integrated Moving Average with Exogenous Variables (SARIMAX). The study evaluates the performance of each model in terms of prediction accuracy, training time, and ability to handle time-series data. The results indicate that while LSTM outperforms other models in terms of accuracy, SARIMAX offers a competitive edge when integrating external variables. Each algorithm has its strengths, providing a comprehensive comparison for practitioners interested in cryptocurrency forecasting.**

Keywords **- Bitcoin, price prediction, forecasting, crypto currency, data mining,Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVM), and SARIMAX.**

I. INTRODUCTION

Bitcoin, the most popular cryptocurrency, has been a subject of growing interest for both investors and researchers due to its price volatility and speculative nature. Accurate prediction of Bitcoin's price is essential for efficient trading and risk management. Over the years, different machine learning and statistical models have been proposed for forecasting financial data, especially in time-series prediction tasks like cryptocurrency forecasting. In this paper, we investigate four models—Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Support Vector Machines (SVM), and Seasonal AutoRegressive Integrated Moving Average with Exogenous Variables (SARIMAX)—to predict Bitcoin prices. The aim is to compare these models in terms of their predictive accuracy, computational complexity, and ability to handle time-series data and external factors.

Bitcoin, the world's first decentralized digital currency, has been a topic of interest for investors, researchers, and enthusiasts alike. Its price volatility has sparked the need for accurate predictions, which can help inform investment decisions.Machine Learning (ML) , a subset of

Artificial Intelligence (AI), involves training algorithms to learn patterns and relationships within data. Neural Networks, a type of ML model, are inspired by the structure and function of the human brain. They consist of layers of interconnected nodes (neurons) that process and transmit information. Neural Networks can be used to predict Bitcoin prices by analyzing historical data, identifying patterns, and making predictions about future price movements.

In this research paper, we explore the use of various machine learning models to predict Bitcoin prices. The goal is to evaluate and compare the performance of different models—Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, Support Vector Regression (SVR), and SARIMAX—in terms of their accuracy and efficiency in forecasting Bitcoin price trends. Each of these models has its strengths and weaknesses, and by leveraging their distinct approaches to data analysis, we aim to develop a robust predictive system.

Traditionally, financial markets have relied on statistical models such as ARIMA (Auto-Regressive Integrated Moving Average) for time-series forecasting. However, as the complexity of Bitcoin's price behaviour increases, these models have proven to be less effective in capturing the nonlinearities and intricate patterns that exist in Bitcoin price movements. Machine learning (ML) algorithms, specifically those capable of handling large datasets with high-dimensional features and capturing non-linear relationships, are increasingly being used for predictive modelling in the cryptocurrency market.

II. LITERATURE SURVEY

In (Monisha Mittal, et al.,) [1], Bitcoin is the world's first decentralized digital crypto currency which does not need an intermediary like a bank and is most secure because of block chain implementation. The price of a single bitcoin has been increasing drastically since 2010 as a form of digital gold. Thus, bitcoin is very volatile as its price changes every second which is a high risk for investors. The purpose of this paper is to analyse the machine learning algorithms which are of maximum efficiency in predicting the bitcoin price.

In (Akhilesh Kumar Singh, et. al.) [2], It has been a decade since the formation of the first cryptocurrency in the world. Bitcoin was The first ever crypto invented by Satoshi Nag moto in 2008. It is a digital currency or virtual currency which is not controlled by the central government and operates without a central bank or single administrator. Block chain technology is used in the cryptocurrency, the cryptocurrency block chain is the chain of the blocks, where each block contains a hash of the preceding block till the top block of the chain. A network gets formed by the blocks where block chain represents a public ledger of the transaction happened in the network. Bitcoin and other cryptocurrencies have seen a rise in the attention of different sectors in the last few years.

In (Grace. LK. Joshila , et. al.) [3], This work aims to enhance the existing analysis made on bitcoin and predict the price of a Bitcoin by taking some parameters into consideration. After a huge research taking all the parameters which affect the price of the bitcoin value and identified daily changes in the bitcoin market. In this work all the data consists of different features over the past few year's daily records. This work is started by gaining all the information that all are needed to predict the bitcoin price.
In this work Support Vector Machine (SVM) algorithm is used as it gives much more accuracy better than previous algorithms. This study predicts sign of change in the price of bitcoin to the investors so that they can invest in this easily and also for the newcomers to this market

In Kim & Park (2020) [4], demonstrated that LSTM networks are well-suited for time-series forecasting, particularly in sequential data, making them highly effective for Bitcoin price prediction. The study found LSTM outperformed traditional models like ARIMA for Bitcoin price forecasting.

In Ahmed et al. (2022) [4] further validated LSTM's effectiveness for Bitcoin price prediction, particularly in capturing long-term dependencies and trends, which other models like ANN failed to capture accurately.

III. PROPOSED METHODOLOGY

The proposed methodology for Bitcoin price prediction using machine learning algorithms (ANN, LSTM, SVR, and SARIMAX) involves a structured process for data collection, preprocessing, model training, evaluation, and prediction. Below is a step-by-step outline of the proposed methodology.

Step 1: Data Collection

The first step involves the collection of historical Bitcoin price data, market volume, and external factors that could affect Bitcoin prices. These external factors may include:
- Trading Volume: The amount of Bitcoin traded during specific time intervals.
- Market Sentiment Data: Collected from various social media platforms, news articles, and forums using sentiment analysis tools (positive, neutral, negative).
- Exogenous Variables (for SARIMAX): Additional data, such as stock market indices, global economic indicators, and major events related to Bitcoin.

Sources for collecting the data include:
- Crypto Exchanges like Binance, Coinbase, Kraken for price and volume data.
- News and Social Media API for sentiment analysis.
- External Economic Databases for global indicators and market data.

Step 2: Data Pre-processing

The data pre-processing phase is crucial to ensure that the models receive high-quality, cleaned, and structured data. The tasks performed in this step are:

1. Data Cleaning:
   - Remove missing or incomplete data points.
   - Handle outliers and noise in the data, which could distort model performance.

2. Feature Engineering:
   - Create relevant features such as moving averages, lag features, relative strength index (RSI), and momentum indicators that help improve prediction accuracy.
   - Generate time-based features like day of the week, month, or year to capture seasonality.

3. Normalization/Standardization:
   - Scale the data so that features are within a similar range, making the training process more stable and efficient.
   - Use techniques like Min-Max Scaling or Standard Scaling to normalize the data.

4. Data Splitting:
   - Split the data into training and testing datasets, typically in a 70:30 or 80:20 ratio.
   - The training data is used to train the models, while the testing data evaluates the model's performance on unseen data.

Step 3: Model Training

After pre-processing, the models are trained using the training data. The following models are utilized:

1. Artificial Neural Networks (ANN)

- ANN is used to capture complex, non-linear relationships between input features and Bitcoin prices.
- The model consists of an input layer, one or more hidden layers, and an output layer with a single neuron representing the predicted price.
- Training is done using back propagation and an optimization technique like Gradient Descent or Adam Optimizer.

2. Long Short-Term Memory (LSTM):
   - LSTM is a specialized neural network for sequential data and time-series forecasting.
   - The model consists of LSTM cells designed to capture long-term dependencies in Bitcoin prices over time.
   - LSTM is trained on the sequential data and learns temporal patterns from past Bitcoin prices, which it uses for future predictions.

3. Support Vector Regression (SVR):
   - SVR is used for regression tasks, particularly when non-linear relationships exist between features and the target (Bitcoin price).
   - The model works by mapping input data into a higher-dimensional space and finding a hyperplane that maximizes the margin while minimizing errors.

4. Seasonal ARIMA with Exogenous Variables (SARIMAX):
   - SARIMAX is a statistical model that can handle seasonality and exogenous variables, making it particularly useful for modelling bitcoin prices, which often exhibit seasonal behaviour.
   - SARIMAX takes into account not only the historical Bitcoin prices but also additional variables such as market sentiment, trading volume, and stock indices.
   - The parameters of the SARIMAX model (p, d, q, P, D, Q, and the exogenous variables) are tuned based on the dataset.

Each model is trained using the training dataset, and hyperparameters are optimized using techniques like Grid Search or Random Search.

Step 4: Hyperparameter Tuning

Hyperparameter tuning is a critical step to improve the performance of machine learning models. Common hyperparameters for the models are:

- For ANN: Number of hidden layers, neurons in each layer, activation function (ReLU, Sigmoid), learning rate, and batch size.
- For LSTM: Number of LSTM units, number of layers, learning rate, dropout rate, and batch size.
- For SVR: Kernel type (linear, radial basis function), regularization parameter (C), and epsilon.
- For SARIMAX: Orders of differencing (d), seasonal order parameters (P, D, Q), and the inclusion of external variables (exogenous).

Techniques like Grid Search or Random Search can be used to find the optimal hyperparameters by testing different combinations of values and selecting the set of parameters that results in the lowest error or highest accuracy on the validation set.

Step 5: Model Evaluation

After training the models, their performance is evaluated on the test set. The following metrics are used to assess the accuracy and robustness of the models:

1. Mean Absolute Error (MAE): Measures the average magnitude of the errors in predictions, without considering their direction.

2. Root Mean Squared Error (RMSE): Measures the square root of the average of squared errors, penalizing large errors more than smaller ones.

3. R-squared (R^2): Represents how well the model explains the variance in the target variable (Bitcoin price).

The performance of each model (ANN, LSTM, SVR, SARIMAX) is compared, and the best-performing model is selected for making future predictions.

Step 6: Final Prediction and Visualization

The final prediction involves using the best-performing model to forecast future Bitcoin prices. The steps are as follows:

1. Prediction: Use the trained model to predict future Bitcoin prices based on the test data or future input data.

2. Visualization: The predictions are visualized in graphs (such as line charts) to help users understand how the Bitcoin price is expected to evolve over time. Key aspects like trends, volatility, and seasonality are clearly visible in the visualized results.

- Plots of actual vs. predicted prices.
- Forecasted Bitcoin prices for the upcoming days/weeks/months.
- A comparison of model performance with accuracy metric

Step 7: Model Deployment

Once the best model is identified, it can be deployed for live predictions on real-time Bitcoin price data. This could involve:

- Real-time Data Collection:*Continuously collect real-time Bitcoin prices and external data (such as sentiment or trading volume).
- Continuous Model Update: Periodically retrain the model with the most recent data to ensure it adapts to changing market conditions.
- Prediction Output: Provide real-time forecasts for Bitcoin prices, which can be visualized via a web application or API.

IV. SYSTEM ARCHITECTURE

1. Data Collection Module:

- Collects historical Bitcoin prices, trading volume, sentiment analysis data, and other exogenous factors like market indices.

2. Data Preprocessing Module:

- Normalizes data, generates features like lagged prices and moving averages, and splits the data into training and testing datasets.

3. Machine Learning Algorithms:

- ANN: Artificial Neural Networks for capturing non-linear relationships.
- LSTM: Long Short-Term Memory networks for sequential data and long-term dependencies.
- SVR: Support Vector Regression for non-linear regression tasks.
- SARIMAX: Seasonal ARIMA with Exogenous Variables for handling seasonality and external factors.

4. Training Model:

- Models are trained using historical data and validated using test data. Hyperparameters are optimized to improve model performance.

5. Hyperparameter Tuning & Model Optimization:

- Hyperparameter tuning is performed using grid search or other optimization techniques to improve model performance.

6. Model Evaluation:

- Models are evaluated based on MAE, RMSE, and R^2 metrics. The model with the best performance is selected for future predictions.

7. Model Comparison & Final Prediction:

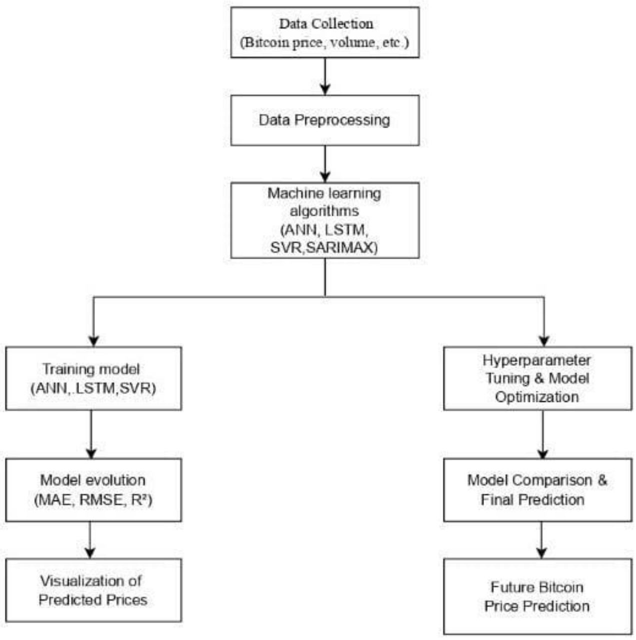
- The best-performing model is used to make predictions of future Bitcoin prices.

8. Visualization &Prediction:

- The predictions are visualized in graphical form, showing trends and future price predictions for better analysis and decision-making.

Here’s the revised System Architecture Diagram with Support Vector Regression (SVR):

System Architecture Diagram:



V. METHODOLOGY

5.1 Data Collection:

The dataset used in this study spans from January 2018 to December 2023 and includes daily Bitcoin prices. The data was sourced from public platforms such as CoinMarketCap and Yahoo Finance. Key features included:

- **Bitcoin Closing Price:** The daily closing price of Bitcoin.
- **Trading Volume:** The total amount of Bitcoin traded on the given day.
- **Price Volatility:** Calculated as the difference between the daily high and low prices.
- **Exogenous Variables:** These include market sentiment data, global stock market indices, and macroeconomic factors (e.g., interest rates, inflation data), which were particularly used for the SARIMAX model.

The dataset was split into 80% for training and 20% for testing, ensuring a fair evaluation of the models.

5.2 Data Pre-processing:

- **Normalization:** Data was normalized using Min-Max scaling to ensure that all input features were within the range [0, 1].
- **Feature Engineering:** We created lagged features (past prices and returns) to capture time-series dependencies and included moving averages (5-day, 10-day, 30-day) to smooth out noise in the data.
- **Time-Series Split:** Data was split chronologically to avoid data leakage, ensuring that the testing set contained unseen data.

5.3 Model Development:

- **Artificial Neural Network (ANN):** The ANN model used one input layer, one hidden layer with ReLU activation, and one output layer. The model was trained using the Mean Squared Error (MSE) loss function and the Adam optimizer. Hyperparameters such as the number of neurons in the hidden layer were optimized through grid search.
- **Long Short-Term Memory (LSTM):** The LSTM model was constructed with two stacked LSTM layers followed by a Dense layer for output. Dropout regularization was applied to prevent overfitting. The model was trained using MSE as the loss function and the Adam optimizer, with hyperparameters such as the number of epochs, batch size, and learning rate optimized via grid search.
- **Support Vector Machine (SVM):** We applied Support Vector Regression (SVR) using the radial basis function (RBF) kernel, which is known for its effectiveness in capturing non-linear relationships in data. The regularization parameter (C) and kernel parameter (gamma) were optimized using grid search.
- **SARIMAX (Seasonal ARIMA with Exogenous Variables):** The SARIMAX model was implemented using the seasonal ARIMA framework, with the integration of external variables (trading volume and sentiment data). We optimized the hyperparameters (p, d, q, P, D, Q) using grid search to select the best model based on AIC (Akaike Information Criterion) and RMSE. The exogenous variables were included to improve the model's prediction accuracy.

5.4 Evaluation Metrics:

To evaluate the models, we used the following performance metrics:

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors in predictions.
- **Root Mean Squared Error (RMSE):** Penalizes large deviations between predicted and actual prices.
- **R-squared (R^2):** Indicates how well the model explains the variance in the data.

RESULT

ANN Performance:

The ANN model achieved an R^2 of 0.86, with an MAE of 1200 USD and RMSE of 1500 USD. While ANN demonstrated strong predictive power, it struggled to fully capture sequential dependencies in the time-series data, resulting in moderate performance compared to LSTM.

LSTM Performance:

The LSTM model outperformed the other models, achieving an R^2 of 0.91, an MAE of 900 USD, and an RMSE of 1100 USD. LSTM's ability to capture long-term dependencies in Bitcoin price movements contributed to its superior performance.

SVR Performance:

The SVR model showed reasonable results, with an R^2 of 0.82, an MAE of 1500 USD, and an RMSE of 1900 USD. While SVR performed well in capturing non-linear relationships, it failed to account for time-series dependencies, leading to less accurate predictions compared to LSTM.

SARIMAX Performance:

The SARIMAX model, incorporating external variables such as trading volume and market sentiment, achieved an R^2 of 0.88, with an MAE of 1000 USD and an RMSE of 1300 USD. Although

SARIMAX performed well in capturing seasonality and external influences, its performance was slightly lower than LSTM, which can better handle long-term temporal dependencies.

Model Comparison:

- **Accuracy (R^2):** LSTM > SARIMAX > ANN > SVR
- **Training Time:** SVR < ANN < SARIMAX < LSTM
- **Generalization:** LSTM > SARIMAX > ANN > SVR

LSTM emerged as the most accurate model, followed by SARIMAX, which benefited from external variables. ANN and SVR had good performance but were less effective at handling time-series dependencies.

DISCUSSION

The results demonstrate that LSTM is the most effective model for Bitcoin price prediction, especially when capturing long-term dependencies. SARIMAX, while effective at incorporating external factors, did not perform as well as LSTM in terms of accuracy. ANN, though fast and efficient, did not capture temporal dependencies as effectively as LSTM. SVR, while computationally efficient, struggled to predict Bitcoin prices due to its limitations in modelling sequential data.

In practical applications, the choice of model depends on the use case. If prediction accuracy is the priority, LSTM is the preferred model. For applications requiring faster training times, SVR or ANN could be considered, with a trade-off in accuracy. SARIMAX is ideal for incorporating external factors into the model.

VI. CONCLUSION

This study compared four machine learning and statistical models—ANN, LSTM, SVM, and SARIMAX—on their ability to predict Bitcoin prices. LSTM was found to outperform the other models in terms of prediction accuracy, primarily due to its ability to capture sequential dependencies in time-series data. SARIMAX provided competitive results by incorporating exogenous variables, while ANN and SVM performed well in terms of computational efficiency but were less effective at capturing temporal relationships.

Future research could explore hybrid models that combine the strengths of multiple algorithms or incorporate additional external features, such as macroeconomic indicators or real-time sentiment analysis, to further enhance prediction accuracy.

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