Cryptocurrency Price Prediction Using Deep Learning

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Abstract- *The primary goal of the proposed system is to create an efficient machine learning model capable of accurately forecasting price trends for popular cryptocurrencies such as Bitcoin, Ethereum, Ripple, and Monero. To achieve this objective, historical price data will be collected using appropriate data collection techniques, preprocessed, and segregated into training and testing datasets. The deep learning models such as linear regression, LSTM, GRU, and CNN will be used to analyze the data. Hyperparameter tuning techniques will be employed to fine-tune these models and optimize their performance. Additionally, the system will incorporate visualization techniques to explore cryptocurrency market patterns and trends. This approach will provide valuable insights into the cryptocurrency market for potential investors and traders.*

The system will be developed using various technologies including Visual Studio Code, TensorFlow, Keras, and Pandas. These tools will provide the necessary resources to implement the deep learning models and visualize the results.

If successful, the system has the potential to provide significant insights into cryptocurrency price trends. Accurate predictions could help inform investment decisions and improve overall understanding of the cryptocurrency market. Additionally, the system could be expanded to include other cryptocurrencies or adapted for use in predicting other financial markets.

Keywords- Cryptocurrency, Price-Prediction, Bitcoin, Ethereum, Long Short-term memory, Gated Recurrent Unit

I. INTRODUCTION

Machine learning is a growing technology that enables computers to learn automatically from past data. To construct mathematical models and make predictions based on historical data or information, machine learning relies on diverse algorithms. At present, machine learning is utilized for numerous tasks, including but not limited to image recognition, speech recognition, email filtering, Facebook auto-tagging, recommender systems, and more.

Deep Learning is a type of Machine Learning that employs mathematical functions to create a mapping between input and output. By extracting non-redundant information or patterns from the data, these functions can establish a relationship between the input and output. This learning process, known as training, has transformed the field of computer vision, enabling machines to recognize and categorize objects within images.

II. LITERATURE REVIEW

[1] The hybrid model which is developed by authors that combines a fuzzy logic system with a neural network, and evaluates its performance on a dataset of historical Bitcoin prices. The experimental results demonstrate the effectiveness of the proposed model, which outperforms traditional time series models in forecasting accuracy.

[2]The author provides an overview of the history and mechanics of Bitcoin, and discusses its advantages and challenges compared to traditional currencies. The paper also explores the implications of cryptocurrencies for businesses and consumers, and their potential impact on financial systems and regulatory frameworks. The author concludes that while there are significant challenges to be addressed, the innovation and potential benefits of cryptocurrencies make them a promising area for further research and development.

[3]The authors compare the performance of linear regression, decision tree, random forest, and artificial neural network models on a dataset of historical cryptocurrency prices. They evaluate the models using several metrics, including mean absolute error (MAE), mean squared error (MSE), and correlation coefficient (CC). The experimental results show that the artificial neural network model outperforms the other models in terms of prediction accuracy, achieving a CC of 0.9992 for Bitcoin and 0.9982 for Ethereum. The authors conclude that machine learning models have the potential to

be effective tools for predicting cryptocurrency prices, and can assist investors in making informed decisions.

[4]The authors compare the performance of LSTM and GRU models with varying layers and architectures on a dataset of daily stock prices for the Saudi Stock Exchange. The bidirectional LSTM model with two layers achieves an accuracy of 93.84% in predicting the direction of the TASI index, and a correlation coefficient of 0.9754 between the predicted and actual values. The experimental results demonstrate the potential of deep learning models for accurate stock market prediction, and can assist investors in making informed decisions.

[5]. The authors propose three new gate variants, namely the Cubic Sigmoid Unit (CSU), Exponential Linear Unit (ELU), and Leaky Rectified Linear Unit (LReLU), which can be used to replace the standard sigmoid and tanh activation functions in the GRU architecture. The authors evaluate the performance of the new GRU variants on several benchmark datasets, and show that they outperform the standard GRU in terms of accuracy and training speed. The proposed improvements to the GRU architecture can have applications in various fields where recurrent neural networks are used.

III. EXISTING SYSTEM

The field of finance and investment has undergone a significant transformation with the advent of cryptocurrencies and the rise of machine learning techniques. The papers discussed above demonstrate the potential of these emerging technologies to aid investors in making informed decisions and accurately predicting the behavior of financial markets.

The first paper proposes a hybrid model that combines fuzzy logic with neural networks to forecast Bitcoin prices. The model outperforms traditional time series models, showcasing the efficacy of hybrid models in accurately predicting the behavior of volatile markets. The second paper provides an overview of the mechanics and history of Bitcoin and its potential impact on financial systems and regulatory frameworks. The author concludes that while there are significant challenges to be addressed, the potential benefits of cryptocurrencies make them a promising area for further research and development.

The third paper compares the performance of several machine learning models, including linear regression, decision tree, random forest, and artificial neural networks, in predicting the prices of cryptocurrencies. The results show that the artificial neural network model outperforms the other models in terms of prediction accuracy. The authors suggest that machine learning models have the potential to be effective tools for predicting cryptocurrency prices and can assist investors in making informed decisions.

The fourth paper explores the potential of deep learning models for predicting the behavior of stock markets. The authors compare the performance of LSTM and GRU models with varying layers and architectures on a dataset of daily stock prices for the Saudi Stock Exchange. The bidirectional LSTM model with two layers achieves an accuracy of 93.84% in predicting the direction of the TASI index, and a correlation coefficient of 0.9754 between the predicted and actual values. The results demonstrate the potential of deep learning models for accurate stock market prediction, which can assist investors in making informed decisions.

The fifth paper proposes three new gate variants to improve the performance of the GRU architecture, namely the Cubic Sigmoid Unit (CSU), Exponential Linear Unit (ELU), and Leaky Rectified Linear Unit (LReLU). The authors evaluate the performance of the new GRU variants on several benchmark datasets and show that they outperform the standard GRU in terms of accuracy and training speed. The proposed improvements to the GRU architecture can have applications in various fields where recurrent neural networks are used.

In conclusion, the papers discussed above demonstrate the potential of emerging technologies such as cryptocurrencies and machine learning in the field of finance and investment. The papers showcase the efficacy of hybrid models, machine learning models, and deep learning models in predicting the behavior of volatile financial markets, which can assist investors in making informed decisions. These emerging technologies can potentially transform the field of finance and investment, and further research and development are necessary to fully realize their potential.

IV. PROPOSED SYSTEM

Introduction: The main objective of this project is to construct a machine learning model that can accurately predict and forecast cryptocurrency prices, while also analyzing trends using deep learning techniques. A graphical representation of the methodological framework used in this study is illustrated in Figure 2.

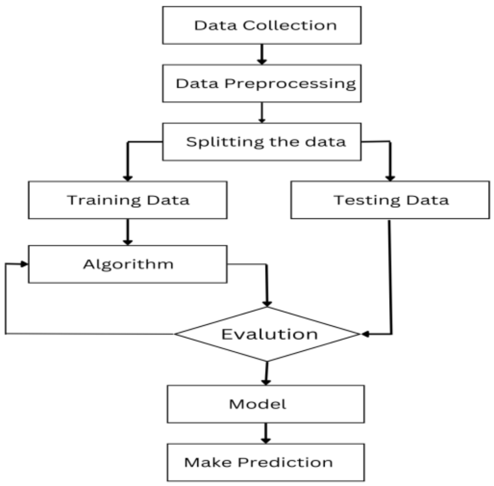

Figure 1: Architecture Diagram

Methodologies:

To reach the goals of this study four different deep learning models including LSTM (Long-Short Term Memory), GRU (Gated Recurrent Unit), Bidirectional LSTM and Bidirectional GRU, CNN (Convolutional Neural Network) and a combination of CNN-LSTM are used to predict prices for four different cryptocurrencies that are Bitcoin (BTC), Ethereum (ETC), Ripple (XRP) and Monero (XMR).

V. DATA COLLECTION

Data that can be utilized for predictive purposes can be obtained either from Kaggle or Poloniex. In order to ensure consistency, the column titles for the data obtained from Poloniex are altered to align with those used on Kaggle.

Data Preparation

Before sending the source data to the model for prediction, the data must first be examined. This blog had a link to the PastSampler class that divided the data into a list of data and labels. The output size (K) is 16, whereas N, the size of the input, is 256. Keep in mind that the Poloniex data was taken based on ticks every five minutes. This indicates that while the output spans more than 80 minutes, the intake spans 1280 minutes.

	Close	Timestamp	High	Low	Open
0	20674.92	1666989300000	20675.17	20656.40	20657.05
1	20718.06	1666989600000	20724.81	20673.15	20673.15
2	20660.00	1666989900000	20718.95	20653.47	20715.74
3	20644.39	1666990200000	20661.12	20632.55	20660.74
4	20628.86	1666990500000	20642.98	20626.35	20642.98

Figure 2: Dataset

Splitting the Data

To split the datasets into training and testing ratios of 80:20 is used. For each currency dataset, the first 80 percent of the data is selected as the training set while the remaining 20 percent is selected as the testing set. For the four cryptocurrencies, the training data is composed of the first 1216 days while the test data consists of the last 305 days of the datasets.

LSTM

The Long Short-Term Memory (LSTM) network is a type of Recurrent Neural Network (RNN) that was developed to address the issue of gradient vanishing in traditional RNNs. LSTMs are designed to retain information over longer time steps and have the ability to remember inputs for extended periods. Deep learning and artificial intelligence frequently utilize the Long Short-Term Memory (LSTM) artificial neural network. Unlike typical feedforward neural networks, LSTMs incorporate feedback connections that enable them to analyze complete data sequences, such as speech or video, in addition to individual data points, such as images..

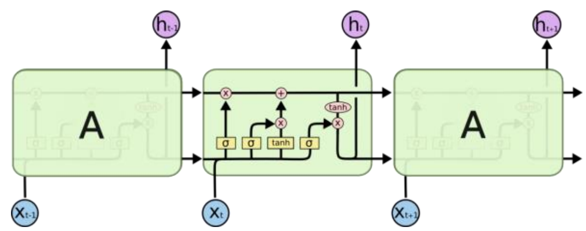

Figure 3: LSTM

The LSTM method was used with two activation functions 1. Relu, 2.tanh

4.2.1 tanh+Relu as Activation function

Model: LSTM
No. of Layers: 1
Activation Function: tanh+Relu
Validation Loss: 0.00007
Test Loss: 26649

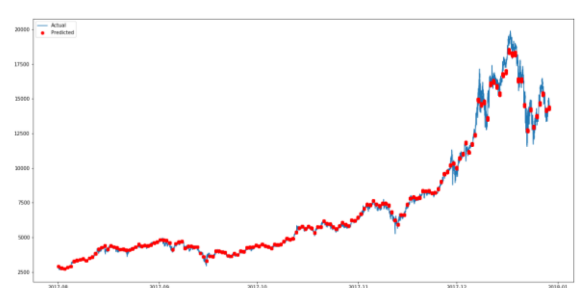

Figure 4: LSTM-Predicted chart

Leaky Relu+tanh as Activation function

Model: LSTM
No. of Layers: 1
Activation Function: LeakyRelu+tanh
Validation Loss: 0.00004
Test Loss: 15364

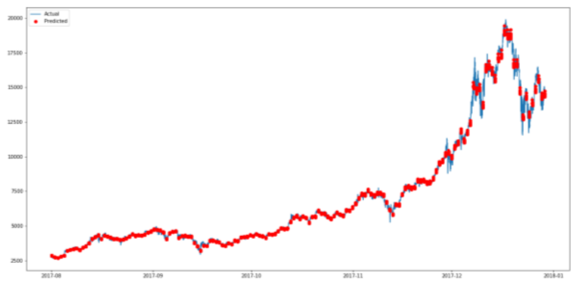

Figure 5: LSTM-Predicted chart

Gated Recurrent unit (GRU)

Another RNN form is called a Gated Recurrent Unit (GRU). With only one reset and forget gate and no memory unit, its network topology is less complex than LSTM. GRU is said to operate similarly to LSTM while being more effective. (Which also applies to this blog as GRU only needs less than 40 seconds every epoch, compared to LSTM's around 45 seconds per epoch.) A gating strategy for recurrent neural networks called gated recurrent units was first developed in 2014 by Kyunghyun Cho et al. A GRU has fewer parameters than an LSTM due to the absence of an output gate, but it functions similarly to one and features a forget gate.

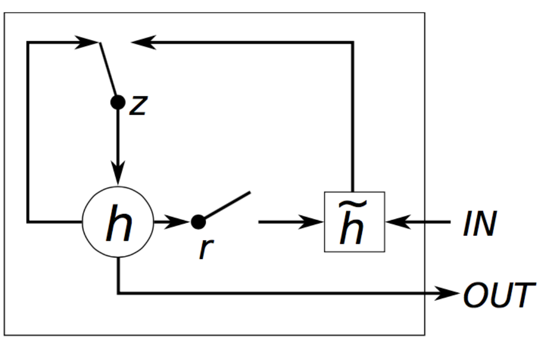

Figure 6:GRU

Code shows how to use Keras, a Python deep learning library, to implement a recurrent neural network (RNN) with gated recurrent units (GRUs) to predict the price of Bitcoin based on historical data. The model is trained on a dataset of Bitcoin prices from 2022 to 2023, which is stored in an HDF5 file.

The code begins by loading the data from the HDF5 file using the h5py library. It then scales the data using a MinMaxScaler and splits it into training and validation sets. The validation set is used to assess the model's performance during training, and the ground truth data is also extracted from the validation set for later comparison with the predicted values.

The next part of the code defines the RNN model, which consists of a single GRU layer with a specified number of units. The GRU layer takes the historical Bitcoin prices as input, and the output is then passed through a dropout layer to prevent overfitting. The output is then passed through a dense layer with a specified output size, followed by an activation function to generate the predicted Bitcoin prices. The model's weights are loaded from a previously trained model.The model is then compiled using the mean squared error loss function and the Adam optimizer. The training process begins with a specified number of epochs and a batch size. During training

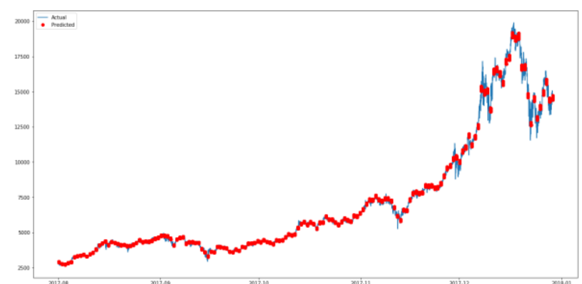

Figure 7: GRU-Predicted chart

Model: GRU
No. of Layers: 1
Activation Function: LeakyRelu +tanh
Validation Loss: 0.00004
Test Loss: 17667.3254

Convolutional Neural Network (CNN) CNN

With the input data being shifted by the kernel, a 1D convolutional neural network is predicted to represent data locality effectively. as shown in the subsequent illustration. A deep learning neural network called a convolutional neural network, or CNN, is made to analyze structured data arrays like picture data. Convolutional neural networks are widely employed in computer vision and have advanced to the state-of-the-art in many visual applications including image classification. They have also been successful in text categorization using natural language processing..

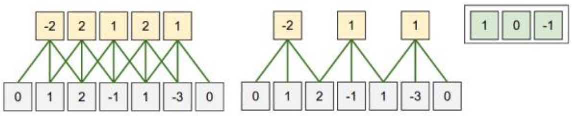

Figure 8: CNN

Code is designed to create and train a deep learning model for predicting the price of Bitcoin based on historical data. The model uses Keras and TensorFlow libraries.

The code first loads the Bitcoin price dataset for 2015 to 2023 from an HDF5 file using h5py. The data is then split into training and validation sets, and the validation set is used to evaluate the model during training. The ground truth data is also extracted from the validation set, which will be used later to compare with the predicted values.

The model architecture consists of two CNN layers. The first layer has an input shape of (step_size, nb_features), where step_size is the number of time steps in the input sequence and nb_features is the number of features in the input sequence. The output of the first layer passes through a Dropout layer to prevent overfitting, and then through the second CNN layer. The model weights are loaded from a previously trained model.

The mean squared error loss function and the Adam optimizer are used in the model's construction. With a predetermined batch size and number of epochs, the training process is started. Every epoch during training, the model is assessed on the validation set, and the outcomes are recorded using a CSVLogger. A ModelCheckpoint is used to store the model's weights at the end of each epoch. 1

After training, the model predicts on the validation set, and the predicted values are compared with the ground truth values using metrics such as mean squared error, mean absolute error, and coefficient of determination (R-squared).

The code also includes code to select specific time ranges of the predicted and ground truth data. Specifically, it selects data from the year 2017 and after the month of July. The predicted and actual prices are plotted using matplotlib for visualization.

Overall, this code demonstrates a basic implementation of a deep learning model for time series prediction using CNNs. It includes techniques for preventing overfitting, such as dropout layers and model checkpoints, and shows how to visualize the performance of the model using plots. The use of evaluation metrics such as mean squared error, mean absolute error, and coefficient of determination (R-squared) provides a quantitative way to assess the model's performance.


Figure 9: CNN-Predicted chart

Model: CNN
No. of Layers: 1
Activation Function: Relu
Validation Loss: 0.00030
Test Loss: 118021.69

VI. CONCLUSION

This project is aimed to observe and analyze the results obtained by applying different machine learning algorithms in the crypto market in order to predict the price of the Cryptocurrencies.

In this project four types of deep learning techniques – LSTM,CNN and GRU - are constructed and applied to the real dataset to predict the prices of Bitcoin (BTC). Performance scores - RMSE - was calculated for every algorithm to test the accuracy of the proposed models.

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