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# Analysis of Crypto Currency Value Using Artificial Intelligence Framework

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**ABSTRACT:** The function of Cryptocurrency has been surely vital in reshaping the economic machine because of its growing famous attraction and global acceptance. A lot of humans have began out to invest in Cryptocurrency, however the dynamical features, uncertainty, and predictability of Cryptocurrency are nevertheless primarily unknown, which dramatically dangers the investments. It is an issue of looking to apprehend the elements that have an impact on the price formation. In this study, we use superior synthetic intelligence frameworks of Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) to expect the rate of various cryptocurrencies. We discover that ANN has a tendency to depend extra on long-time period records at the same time as LSTM has a tendency to depend extra on short-time period dynamics, which imply the performance of LSTM to make use of beneficial records hidden in historic reminiscence is more potent than ANN. However, given sufficient historic records ANN can acquire a comparable accuracy, as compared with LSTM. Evaluation of those algorithms is finished to decide higher prediction to investigate the rate dynamics of various cryptocurrencies inclusive of Bitcoin, Ethereum, and Ripple. However, the rationale of the predictability may want to range relying at the layout of the machine-studying version that's implemented.

## I. INTRODUCTION

The first decentralized virtual forex or cryptocurrency, which changed into delivered in 2008 in a paper through creator Satoshi Nakamoto, changed into Bitcoin. Bitcoin is one of the maximum precious cryptocurrencies withinside the world. A cryptocurrency in essence is a virtual asset that means it exists in a binary layout and is derived with the proper to apply and the information that don't own that proper aren't taken into consideration assets, and it's far designed to paintings as a technique of change that makes use of sturdy cryptography to make sure dependable economic transactions, and substantiate the switch of assets. After the discharge of Bitcoin in 2009, over 4000 opportunity versions of Bitcoin which can be mentioned as "altcoins" were created. Over the beyond few months, the cryptocurrency marketplace has long gone via extensive volatility. Volatility as a percentage of fee fluctuations, it considerably influences change methods and funding picks simply as on opportunity figuring out and proportions of essential risk. The really well worth of all one of a kind cryptocurrencies fluctuates honestly like a inventory aleven though in an sudden way. There are diverse calculations applied on economic change facts for fee forecasts. Notwithstanding, the parameters influencing cryptocurrencies are extraordinary. In this way it's far crucial to forecast the estimation of various cryptocurrencies so the proper choice may be made. The price of those cryptocurrencies would not depend on commercial enterprise activities or mediating the government, in no way like securities exchanges. Hence, to expect the really well worth we sense it's far very crucial to apply AI innovation to foresee the price of various cryptocurrencies.

## II. LITERATURE SURVEY

Greaves, A., & Au, B proposed Bitcoin is the world's main cryptocurrency, permitting customers to make transactions securely and anonymously over the Internet. In current years, The Bitcoin the environment has won the eye of consumers, businesses, buyers and speculators alike. While there was vast studies completed to investigate the



community topology of the Bitcoin community, restricted studies has been executed to investigate the community's have an effect on on average Bitcoin charge. In this paper, we check out the predictive strength of blockchain community-primarily based totally functions at the destiny charge of Bitcoin. As a end result of blockchain-community primarily based totally function engineering and gadget gaining knowledge of optimization, we gain up-down Bitcoin charge motion type accuracy of approximately 55%. Hayes, A. S. goals to discover the in all likelihood source(s) of fee that cryptocurrencies show off withinside the market the usage of pass sectional empirical facts analyzing sixty six of the maximum used such 'coins'. A regression version changed into anticipated that factors to a few principal drivers of cryptocurrency fee: the issue in 'mining 'for coins; the fee of unit manufacturing; and the cryptographic set of rules employed. These quantity to relative variations withinside the fee of manufacturing of 1 coin over every other on the margin, keeping all else same. Bitcoin-denominated relative costs have been used, warding off a whole lot of the charge volatility related to the greenback trade fee. The ensuing regression version may be used to higher apprehend the drivers of relative fee located withinside the emergent region of cryptocurrencies. Using the above analysis, a fee of manufacturing version is proposed for valuing bitcoin, wherein the number one enter is electricity. This theoretical version produces beneficial outcomes for each an man or woman producer, with the aid of using placing breakeven factors to begin and prevent manufacturing, and for the bitcoin trade fee on a macro level. Bitcoin manufacturing appears to resemble a aggressive commodity market; in concept miners will produce till their marginal charges same their marginal product. H.White supplied of a few outcomes of an ongoing venture the usage of neural-community modeling and gaining knowledge of strategies to look for and decode nonlinear regularities in asset charge movements. The writer specializes in the case of IBM not unusualplace inventory day by day returns. Having to address the salient functions of monetary facts highlights the position to be performed with the aid of using statistical inference and calls for adjustments to conventional gaining knowledge of strategies which might also additionally show beneficial in different contexts. Kaastra and M. Boyd Artificial neural networks are regularly occurring and tremendously bendy characteristic approximators first used withinside the fields of cognitive technology and engineering. In current years, neural community packages in finance for such responsibilities as sample recognition, type, and time collection forecasting have dramatically increased. However, the massive wide variety of parameters that ought to be decided on to increase a neural community forecasting version have intended that the layout procedure nonetheless entails a whole lot trial and error. The goal of this paper is to offer a realistic introductory manual withinside the layout of a neural community for forecasting monetary time collection facts. An eight-step system to layout a neural community forecasting version is defined such as a dialogue of tradeoffs in parameter selection, a few not unusualplace pitfalls, and factors of war of words amongst practitioners.

### III. PROPOSED METHODOLOGY

The ancient charges facts for cryptocurrencies had been amassed from blockchain markets, and the overall variety of samples is 1030 buying and selling days among seventh August 2015 to second June 2018. The charge facts made out of 4 factors specifically starting, high, low, ultimate charges. In this study, we examine the charge of 3 of the maximum famous cryptocurrencies: Bitcoin, Ethereum and Ripple. We take the 4 factors because the center of our model, after which expect the following couple of days starting charge which became used because the output of the model. We pick out the outlet charge because the output for it displays all of the preceding reminiscences and events.

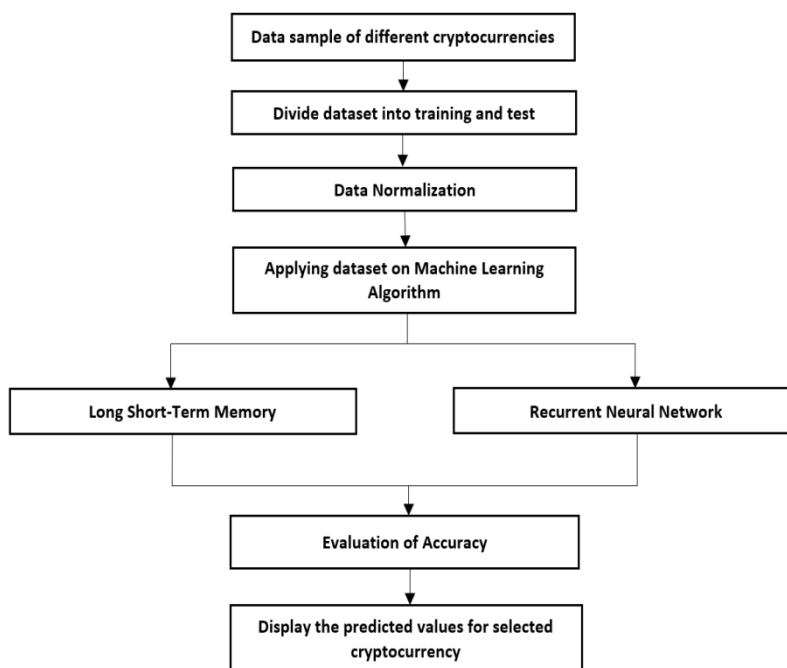


Figure 1: Overview of system

The dataset was divided into training and testing sets according to an 80%, 20% ratio as this can avoid overfitting during de model training. The mean price of the three cryptocurrencies: Bitcoin \$ 3082.084, Ethereum \$ 194.810, Ripple \$ 0.223, and the 95% confidence interval of their historical price: [2834.034, 3330.134], [176.977, 212.642], [0.196, 0.248]. As is shown in Figure 1, Bitcoin and Ethereum price have sharp fluctuations, and their standard deviations are as high as 4063, 292, 0.43 respectively.

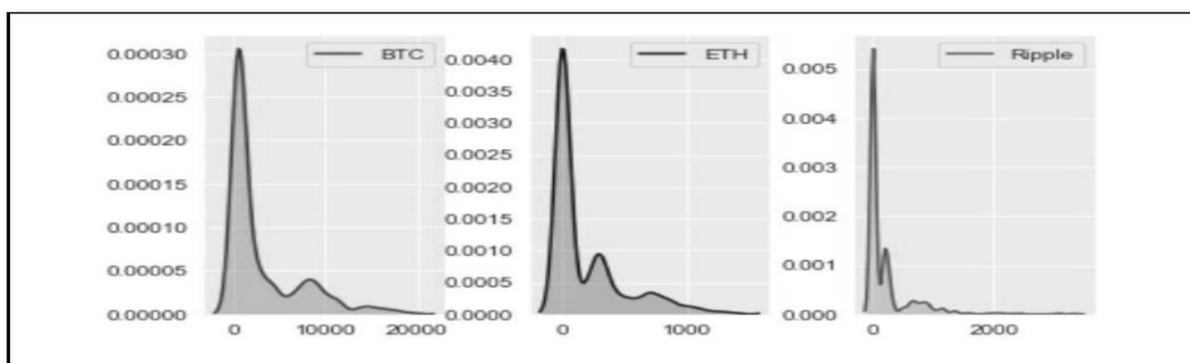


Fig-2: Density distribution of the price history from 7th August 2015 to 2nd June 2018, for Bitcoin (left panel), Ethereum (middle panel), and Ripple (right panel), respectively.

A. ALGORITHMS

Some works were said at the forecasting of monetary markets the use of deep neural networks. In this examine, we rent triumphing deep gaining knowledge of fashions to examine and are expecting crypto currencies rate dynamics, such as fully-related Artificial Neural Network (ANN) and Long-Short-Term-Memory (LSTM) Recurrent Neural Network. For the LSTM, it consists of 3 layers, every having ten nodes. Each LSTM mobileular kingdom carries 3 gates: a overlook gate, an enter gate, and an output gate. LSTM controls the loss or addition of facts thru the gate to acquire the characteristic of ignoring or reminiscence.



$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

The overlook gate is a Sigmoid characteristic which has the enter  $h_{t-1}$  and  $x_t$  wherein the previous is the output of the closing unit, and the latter is the enter of this unit. The Sigmoid characteristic can produce feet that's a price in  $[0,1]$  for every object in  $C_{t-1}$  (inner kingdom), '0' manner that 'hold this completely' and '1' represents 'overlook this completely', to govern the quantity of forgetting of the closing unit.

An enter gate produces it thru a Sigmoid activation, and the tanh characteristic that generates capacity inner kingdom ( $C_t$ ). Both of them manipulate how lots new facts could be introduced to  $C_{t-1}$  to replace the actual inner kingdom to  $C_t$ :

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\vec{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \vec{C}_t \quad (4)$$

The output gate  $O_t$  makes use of a Sigmoid characteristic to decide which a part of neuron kingdom want to be output, after which we want to transform  $C_t$  to output  $h_{t-1}$ :

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t * \tanh(C_t) \quad (6)$$

The ANN version used on this examine is a fully-related multi-layer perceptron that imitates the shape and characteristic of the human brain, and it has a robust capacity of in approximating non-linear information. In this experiment, our ANN version has 3 components: the enter layer, hidden layer, and output layer. Each layer has ten nodes. The enter layer offers a weight  $w_{ij}$  to the enter, and there may be an activation characteristic-Sigmoid characteristic  $f$ . Then  $x_i$  the output of the hidden layer could be surpassed to the output layer that's similar to the closing process, after which we are able to get the very last output.

$$y_i = f(X_i) = f\left(\sum_{j=1}^n w_{ij} x_j\right) \quad (7)$$

$$f(x) = \frac{1}{1 + e^{-x}} \quad (8)$$

We use the ancient information to are expecting the fashion of the cryptocurrency market, however what can the ancient reminiscence duration that we use produce the maximum applicable results? With the identical duration of ancient reminiscence, will the unique variety of reminiscence that we need to are expecting impact the accuracy of the version? We examine the maximum suitable inner reminiscence and predictive reminiscence duration in information the cryptocurrency rate dynamics. We strive 5 unique inner reminiscence lengths: 8, 14, 23, 31, and 56 days, after which integrate with 5 predictive reminiscence lengths: 1, 7,9,14, 21 days

#### i. LSTM Estimate of Time Series Memory

As for the LSTM version, it has a similar overall performance with the ANN version in general, whilst predicting the one-day destiny charges of those cryptocurrencies, primarily based totally on imply rectangular error. It demonstrates that despite the fact that ANN is loss of inner capability, it is able to correctly extract and use the beneficial data hidden withinside the historic charge dynamics to are expecting a destiny charge.. We additionally discover that LSTM required the period of charge records isn't like that of ANN. LSTM commonly opt for brief historic reminiscence. For example, LSTM with seven days of historic reminiscence for Ethereum and Ripple or 14 days of historic reminiscence for Bitcoin carry out the best. The version-information correlation sharply declines because the period of historic reminiscence increase. It shows that LSTM is based the version prediction greater at the maximum current few days.

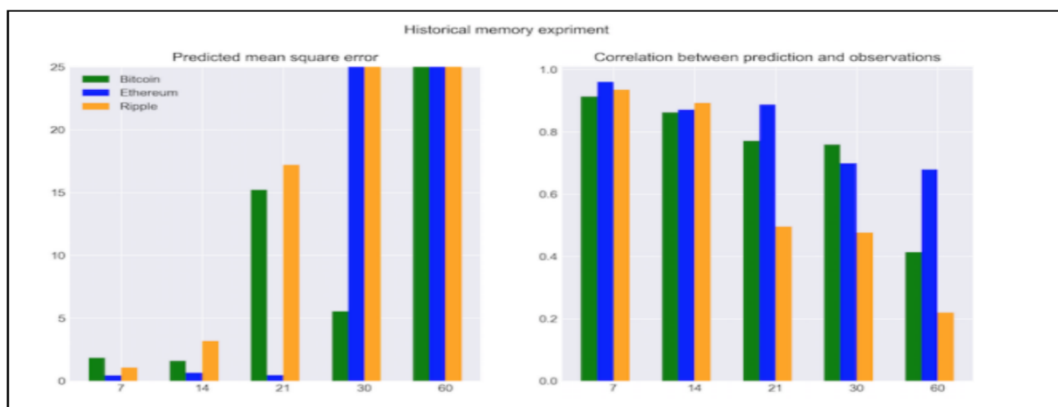


Figure 3: Performance of LSTM model, given 8, 14, 23, 31, and 56 days price history as input features.

Left and proper panels constitute version-facts imply rectangular mistakes and Pearson correlation. In predictive reminiscence experiment, LSTM ought to first-class forecast subsequent day charge of the Bitcoin, Ethereum, and Ripple, the use of their top-quality historic duration of reminiscence diagnosed before. Compared with the ANN version, the LSTM version indicates sizeable fluctuations at the same time as predicting one-of-a-kind lengths of historic costs withinside the future.

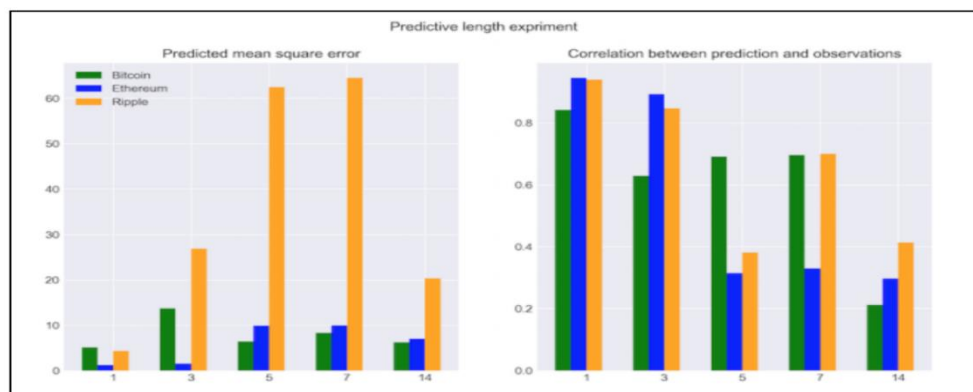


Figure 4: Performance of LSTM model, given 1, 7, 9, 14, 21 days of predictive length.

Left and right panels represent model-data mean square error and Pearson correlation.

#### IV. RESULTS AND DISCUSSION

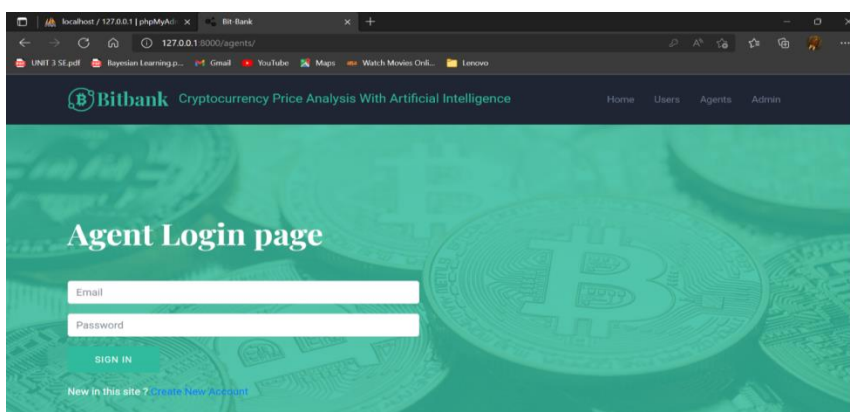


Figure 5: Agent Login Page

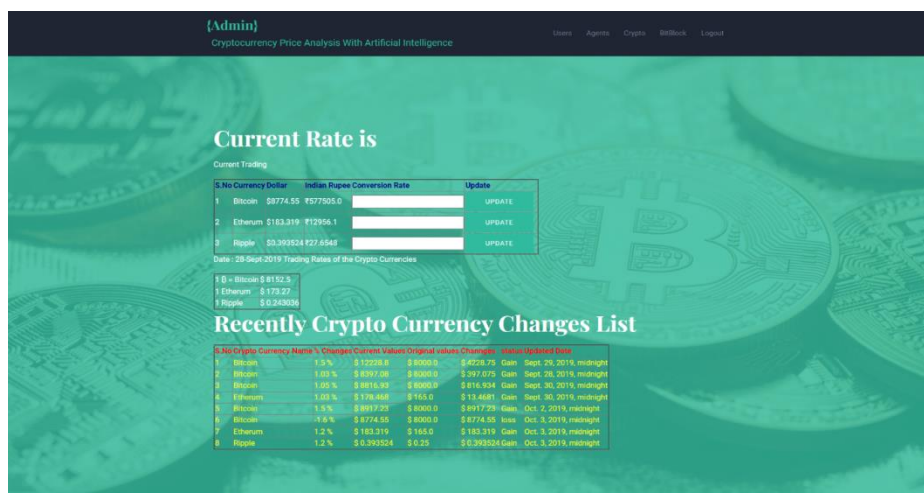


Figure 6: Recent Changes list of Cryptocurrency

## V. CONCLUSION

In this paper, we use two distinct artificial intelligence frameworks, namely, Long Short-Term Memory and Artificial Neural Network to analyze and predict the price dynamics of Bitcoin, Ethereum, Ripple and many more cryptocurrencies. We showed that the LSTM and ANN models are comparable and both reasonably well enough in price prediction, although the internal structures are different. Then we further analyse the influence of historical memory on model prediction. We find that ANN tends to rely more on long-term history while LSTM tends to rely more on short-term dynamics, which indicate the efficiency of LSTM to utilise useful information hidden in historical memory is stronger than ANN. However, given enough historical information ANN can achieve a similar accuracy, compared with LSTM. This study provides a unique demonstration that Cryptocurrency market price is predictable. However, the explanation of the predictability could vary depending on the nature of the involved machine-learning model.

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