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SURVEY ON DEEP LEARNING BASED CRYPTOCURRENCY PRICE PREDICTION

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ABSTRACT

Cryptocurrency is a type of digital money in which histories are kept by a decentralised system employing encryption before centralised expert and financial transactions are confirmed through mining. One of its goals is to provide users and investors more control by decentralising the influence of institutions and organisations. Due to its recent rise in importance, relevance, and influence on people's lives as a result of increasing access, which necessitates systems with strong processors for mining, etc., numerous considerations regarding its adoption have been considered in India. In recent years, Bitcoin has increased in significance as well as in popularity and importance. With significant advancements in this area, many firms around the world have realised how crucial it is to use this technology in order to virtually take advantage of the many numerical benefits. Predictions of stock prices, cryptocurrency prices, and real estate price values and other sectors and domains where it is used In the current financial exchange environment, price prediction is one of the major issues since buyers and sellers of cryptocurrencies face an intriguing conundrum. It appears to have reached previously unheard-of heights in recent years, giving rise to ideas that defend the pattern of its upsurge. Recently, investors, researchers, and other economists have been quite busy trying to figure out if the movements and brief swings of cryptocurrencies can be predicted. In order to enforce these verdicts in the bitcoin market, it is critical to have the most reliable and accurate methods of price prediction, and liability and asset analysis, at least for the near future. We may do this by utilising machine learning models that can recognise long-term dependencies, such as LSTM, RNN etc. Some of the crucial factors used include close price, offered price, low price, high price, market cover and size, as well as relationship between a limited cryptocurrencies. This evaluation is focused on identifying critical factors that influence how unpredictable a transaction is by utilising the system to improve the usability of this practise. It was able to examine ten papers on cryptocurrency and price forecast of commodity that used a variety of methods, including RF, LSTM, ANN, MAPE, and MBE In conclusion, these research have demonstrated an optimally high level of estimating accuracy. In order to be able to accurately estimate the prices, a variety of methodologies and algorithms were used, and these varied significantly amongst the articles. While the majority viewed the issue from a different perspective, a small group continued to work on the conclusions of earlier approaches by adding newer layers. The numerous methods and tactics that our group discussed all seemed to have advantages and disadvantages of their own while being appropriate for particular situations.

Keywords: Mean Bias Error, Long Short-Term Memory, and Artificial Neural Networks

1. INTRODUCTION

Numerous studies have been done on financial market prediction, including the forecast of the Bitcoin market. Since this is a time series prediction problematic in a market that is still in its infancy, emerging cryptocurrencies like Bitcoin, Ethereum, and Litecoin offer an intriguing analogy. As a result, the market is highly volatile, which offers a chance for making predictions. Holt-Winters exponential smoothing models, which are the standard time collection forecast methods, depend on on linear presumptions and need data it can be divided into seasonal, chaos, and momentum components in order to have effect. This approach is more suited for a task like projecting revenue where there are seasonal effects. These tactics aren't particularly effective for this project due to the lack of seasonality and excessive fluctuation in the market for cryptocurrencies like Bitcoin. Machine learning presents since there is no regularity and an intriguing technological solution given the project's complexity based on its overall success in related fields. NLP tasks, it might also be consecutive and have a characteristic that has demonstrated promising results, are included. This kind of problem, which uses consecutive records, is comparable to a price prediction assignment. Due to the superior algorithms' temporal character, recurrent neural networks and LSTM networks are preferred above multilayer perceptrons (MLP). Goal of this work to determine how accurately ML expertise can be used to prediction the rate of cryptocurrencies like bitcoin. There is a dearth of machine learning research on cryptocurrencies like Bitcoin. Because these responsibilities may be seen as equivalent, linking to various financial time series forecast using deep learning is too evaluated. Due to its escalating popularity, it's critical to maintain track of its market price in order to stay informed. This project enables users to receive extensive statistics summaries along with real-time trend changes in the prices of numerous cryptocurrencies.

2. Literature Survey

[1] In this work, three dissimilar ML algorithms are developed and utilised to forecast the values of three different cryptocurrencies—BTC, ETH, and LTC. Enactment evaluations have been done to evaluate how accurate different models are. After that, we contrasted the current and projected prices. Results demonstrate that GRU outperformed the alternative algorithms, with MAPE values for ETH, BTC, and LTC, respectively, of 0.9356%, 0.3342%, and 0.3225%. For ETH, BTC, and LTC, correspondingly, the Root Mean Square Error for the GRU version was found to be 26.59, 174.129, and 0.825. On the basis of those results, the GRU model for the embattled Bitcoin may be regarded as trustworthy and effective. This approach is regarded as the most effective one. Although there are significant changes among the real and forecast costs for both BTC and ETH, bi-LSTM reflects substantially fewer accuracy than GRU and LSTM. The results of the experiment demonstrate the suitability and dependability of the artificial intelligence algorithm for bitcoin prediction. GRU predicts cryptocurrency values more accurately than this algorithm, although all of the algorithms have outstanding forecasting results.

[2] Finding a line that works nicely with the records is the key goal. If a line's overall validation loss is smaller, it is considered to have nice suit. The error in a regression line is the distance between the components. To locate more compact collections of patterned records and forecast the price for the following day, we must concentrate on LSTM and RNN. in order to make the model evaluate. A large number of filtered record sets are required for the records training. When data reaches a stabilisation factor, the outcome performance does not improve; thus, We will enhance it using the feature's loss feature, activating function, and optimizer. The findings are based on training data, and they can be cross-checked using the statistical significance test's current cost.

[3] This work stated that while some recent research studies have used ML to improve the accurateness of the prediction of the price of bitcoin, only a small number appear to have focused on the value of using a range of techniques to inspect various data formats and fundamental properties the creators of article first categorised the value of Bitcoin by several factors, such as daily price and high frequency price, ML approaches are being used to calculate Bitcoin prices on various recurrences. For the calculation of the cost between a 5-minute intermission value, the basic trade features collected from a bitcoin exchange there have employed instead of a group of cross features including gold market price, economy and trading, network and property, and attention. It was also noted that, when compared to the typical results for the daily price prediction, they achieved increased efficiency, with the highest accuracy rates for the statistical approaches and ML algorithms, respectively, being 66% and 65.3%.

One of the main findings was that for a 5-minute estimation of Bitcoin, certain ML methods, such as RF, XGBoost. Outperformed the observed methods, with accuracy rates approaching a amount of 69.3%. In addition, mentioned that their examination of the projection for the price of Bitcoin may be viewed as a miniature study of relevance for ML methods.

Overall, it was found that when compared to the dataset of daily prices, the Logistic Regression and Least Discriminant Analysis approaches performed better than the other ML systems, demonstrating that carefully chosen multi-dimensional characteristic groups can mitigate the discreteness of the systems for the daily value forecast of Bitcoin. This work looked to have some faults, one of which was the use of only two types of data for prediction. In despite the fact that it is truly necessary to gather data on the price with different features having more aspects.

The weighting of the ML algorithms in the research not been carried out, which was another problem. The final point made was that other investigations would focus on a more suitable feature of the view using textual mining along with social cluster studies in order to advance this analysis. Examples of additional methods that would be studied include statistical methods like ARIMA and the Machine Learning model RNN.

[4] In this study, it appears that the closing prices of five companies from a variety of service sectors were predicted using ANN and RF methodologies. Here, additional variables that serve as the system's intake have been created using the financial data that is pertinent to stocks. The systems were categorised using key benchmark indices including MAPE and RMSE. The algorithms' ability to estimate the stock closing price is demonstrated by the reduced rates for the two aforementioned indices.

The study concluded that an ideal system that can identify some fundamental patterns and complex correlations regarding a series of this size is needed for dealing with this kind of data in particular for analysing the stock market. Additionally, An ML method in this area appears to have demonstrated an improvement in efficiency rates of roughly 70%-95% in contrast to earlier methods. To continue with the investigation, prior information from 5 firms was gathered using Yahoo Finance. Additionally, this dataset includes stock knowledge for 10 years of different companies and contains information about their histories. It should be observed that the stock's daily closing price appears to have been retrieved on its own. The correlative investigation using MBE, RMSE, and MAPE results appeared to conclusively show which Artificial Neural Network provided a extra precise assessment of stock prices than RF. Results from the ANN (Artificial Neural Network) model that were exhibited at finer rates had a RMSE of 0.39, a MAPE of 0.88, and an MBE of 0.009. Several of the shortcomings of this article included the exclusion of some elements and the use of fewer parameters, which may have led to the production of better results.

[5] RNN, MLP, and LSTM combined in a hybrid model was employed for the forecast in the study "Deep Neural Networks for Cryptocurrencies Price Prediction". The most accurate method for predicting the directional movements of cryptocurrencies has been determined to be LSTMs. The shortcoming of trend prediction neural networks is that they are unable to comprehend the financial impact of misclassification.

[6] Models like BART, MLP, and RF were employed in the study "Forecasting of Cryptocurrency Prices using Machine Learning." We have verified that the statistical qualities of the bitcoin time series under investigation are not subject to any stringent limits by these models. The average for BART and MLP was mean absolute percentage (MAPE) of about 3.5%, whereas RF had an average An average absolute inaccuracy rate of roughly 6%. The limitation was that the smallest dataset possible was used, which leads us to the conclusion that the prediction accuracy was relatively low. This can be expanded by using a dataset with more fields and values. [7] LSTM, LOG, RF, and GBT models were employed in the study "Time Series Prediction using LSTM Networks and Its Application to Equity Investment." We have shown that the advantages of intricate and computationally demanding LSTM networks can be maximised

by utilising LOG as a baseline. Given that it has the fewest hyperparameters, it is anticipated to be resilient. The theoretical values and the predicted probabilities show good agreement. When doing diversified learning, RF enables you to combine various weak learner types. produces powerful estimators with high performance and lower overfitting risk. Decision trees, which are typically weak learners, are made into extremely accurate learners by GBT using a boosting technique. Weak learners are applied to the sample that has been weighted repeatedly in order for this to operate. The SVM algorithm has several properties Those combine convex expansion with core region expansion, including a potent abstract background, perceptual geometric analysis, and others. Additionally, it generates the ideal separation hyperplane for categorising fresh samples. The LSTM performed nearly as well to the LOG and SVM. The projected probabilities are referred to as predictability since LSTMs are LOG-like discriminative models. Unlike LOG, I ultimately reached the following conclusions. Due to a mismatch between the theoretical values and the projected probability, RF and GBT produced subpar results. He may be using decision trees because he is a slow learner, which could be the source of this. It is difficult to calculate predictability using expected probabilities and to carry out the necessary probability calibration procedures. The SVM outcomes demonstrate balanced behaviour, which includes LOG. SVM is a discriminative feature, while LOG is a discriminative model. As a result, the prediction probability cannot be calculated using SVM.

[8] Many algorithms, including LSTM, GRU, RNN, and many others, are employed in this paper. In this article, the authors examined the market's predictability over a number of time frames, between 1 and 60 minutes. It was discovered after utilizing multiple ML models that it performed better than the random classifier and is appropriate for both prediction tasks and gradient boosting classifier. Scientific feature sets were the most pertinent among the many feature sets used, including blockchain-based, credit-based, and other feature sets. When the prediction scope is expanded, the prediction rate will rise. In this, the ML models are able to show that it is limited and accurately discern the exactitude just above 50%. They are also intelligent to forecast short-term swings of the crytocurrency market. This may be the result of a few factors, such as an instant market response to includes or a vast amount of information that has an impact on the bitcoin market but is unrelated to the features. Prediction accuracy is improved with longer prediction horizons. and pave the way for similar study opportunities. The most significant and precise source of the predictive capacity is yet unknown in these models, which differentiate among the importance of characteristics and utilise a limited number of function sets. It is based on transaction costs and benefits, according to several theoretical equilibrium models, and may have some bearing on the prediction. The most accurate method for predicting the fluctuations of cryptocurrencies is LSTM (1-second and 60-minute forecasting windows). GBC trains individual weights in addition to weighing the intake of numerous decision trees. On the 15-min horizon, GRU's forecasts are more precise. The predicting effectiveness surges for wider temporal scales, judicious use of GBC and RNN, and continued importance of scientific aspects, while for larger forecast scopes, features like transaction per second are ideal and technical features become less important. The systems are capable of anticipating the accuracy movement ranging from 52% to 57%.

[9] Rectilinear regression and the LSTM model are used to forecast bitcoin, according to the authors of the study. ANNs and ML methods are used in this model. ML and AI models are trained using a variety of data sources. Rectilinear regression model accuracy was claimed to be 99.96% accurate, which is quite high when compared to other ML systems. As contrasted to that,, LSTM exhibits a lower error rate of 0.08%. Because of how unpredictable the bitcoin market is, no prediction has ever been completely correct. In general, trend, momentum, and pattern are the prominent topics. Rectilinear regressions use the Mean Squared Equation to assess the validity of the linear graph in relation to the time-frame data set. With a mean absolute error of 0.08 percent, the LSTM model has the potential to determine correctness.

[10] In order to obtain the most crucial features, Dennys et al. used several attribute selection processes and machine learning techniques such ANN, SVM and k-means clustering. This study's drawback, though, is that it solely focuses on investors. Since Bitcoin have the potential to alter the dynamics of the global economy, policymakers should be viewed as a key participant in the system.

[11] Sean McNally et al employed LSTM and a Bayesian improved RNN to forecast the movement of the price of bitcoin in US dollars. To contrast the deep learning techniques, they also employed the ARIMA model.

[12] In Atsalakis et al. this study efforts on computational intelligence method especially combine neurofuzzy controller to be able to forecast the argument rate of bitcoin. This model used neuro-fuzzy method and ANN.

[13] Goodfellow et al. suggested a reinforcement learning work for economic indication exemplification and trading. They collective the RL, DL, and their NN to generate precise prediction results. They authorize the recommended method using commodity future markets in addition to stock market data.

[14] Madan et al. looked into the tendencies around BTC and attempted to forecast the price of bitcoin using machine learning. To forecast the daily price volatility, they used 25 characteristics associated with bitcoin.

[15] Lahmiri et al. used ML techniques to estimate the daily price of cryptocurrencies with high data availability, including digital cash. To obtain the accurate prediction rate of high liquidity cryptocurrencies, they used RNN and GRNN .

[16] Pant et al. Declare that all market evaluations of virtual currencies are affected directly or indirectly by socially generated beliefs about virtual money found on Twitter. This study focuses on using sentiment analysis to predict the fluctuating value of bitcoin and establishing a link among negative and positive opinions.

[17] Nivethitha et al. suggested utilising the LSTM machine learning method to predict future stock prices. Because it is a foundational component of share price prediction and other financial prediction models, they concentrated particularly on time series prediction. And when compared to the outcomes of the current model ARIMA, the LSTM algorithm offers effective and precise results.

3 METHODOLOGIES

The concept of a neural network is fascinating because it teaches the computer to use previous experiences (data) to solve problems at hand. It is based on how the human brain's neural networks function, which send millions of impulses at once and react to situations based on prior knowledge. RNNs are a particular class of NNs that employ loops to preserve information. A RNN can be thought as numerous copies of the same network that are all capable of transmitting the same message from one successor to another. The following network results from unrolling an RNN. The chain-like structure demonstrates how closely sequences and lists are related to RNN. Neural networks are typically designed to apply to such data. Significant progress has been made in the past In the past few years, RNN has been used to tackle a range of problems, such as voice recognition, language processing, interpretation, etc. The use of "LSTM," a very powerful algorithm, allowed for these achievements. unique type of RNN that performs a variety of jobs far better than any conventional version. They are used to achieve nearly all of the RNN-based results mentioned above.

3.1 RNN's long-term dependencies are a drawback.

One of RNN's main selling points the notion that they can link historical data to current endeavour. We can immediately know, without any additional context, that the word will be "East" if we are attempting to forecast the final word of the RNNs can examine the use of the prior knowledge in these circumstances, where there is little time between the right information and the location where it has to be. However, in some circumstances, a minimal context is not enough. Think about guessing the final phrase in the statement, I am proficient in Spanish conversation. The most recent evidence suggests that the following term will surely be a language, but if we so choose restrict which language, we need to know historical context. The time it takes to get the right information and get to where it's needed could grow significantly. Unfortunately, when this limit rises, RNNs are unable to develop the ability to link the data.

3.2 LSTM Networks

LSTM a special type of RNN, are able to recognize long-term enslavements. They are frequently employed in a wide range of issues and provide unexpected outcomes.

Long-term dependency problems are specifically avoided with LSTMs. Their natural ability to retain material for a long period means they don't need to study it attentively. There is a series of adaptive neural network modules in every RNN. This module in a typical RNN has a fairly straightforward structure, like a hyperbolic tan layer. Although recurring modules have various architectures, LSTMs have a similar structure. There are four levels that interact uniquely rather than just one neural network layer.

The cell's condition is depicted by the continuous line that goes through the top of the diagram is the LSTM's key. The way the cell is set up is similar to an assembly line. With only a few minor linear interactions, it moves straight through the chain. Information simply moves forward unchanged. A mechanism known as a gate carefully regulates the ability of LSTMs to delete or insert cell state data. The best way to pass information through is through gates. They are made up of point wise multiplication and a layer of sigmoid neural networks.

4 CONCULSION

Because of external characteristics or external societal aspects that affect price forecasting, researchers have had difficulty projecting bitcoin prices. In addition, forecasts are made using a range of ML and DL methodologies. NNs have demonstrated potential in the forecast of time-series data in recent years. Numerous different types of neural networks may be used to analyse bitcoin prices. It has been discovered that LSTM is the most effective of all of them. This may be as a result of their capacity to remember and extrapolate information's materialistic characteristics. The proposed website interface aims to assist investors in anticipating the variation in pricing of various cryptocurrencies that are occurring in real time, in addition to providing an extensive statistical analysis and rating evaluation of various cryptocurrencies, which could assist them in evaluating a wide range of data regarding the current state of the crypto market. Additionally, it is very likely that the performance of this model can be enhanced by using better and more effective methods as well as additional systems with potent GPUs and a quicker processor, which will undoubtedly increase both the accuracy and training speed of the data.

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