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Cryptocurrency Price Prediction by Integrating Optimization Mechanism to Machine Learning

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***Abstract*—Research is being done right now to try to predict the future value of cryptocurrency. The possibility of using a python-based approach has been explored by the scientific community as a means of realizing this aim. In predictive analytics, it is becoming standard practice to use the same dataset for both training and testing purposes. Traditional studies have been slowed down by problems with precision and efficiency. This research makes use of optimization and the Python programming language to provide a versatile prediction model with little implementation time. Dataset size is decreased when classification is performed in Python, which shortens the training period. Eliminating extraneous information also improves the performance of the trained model. Because of this change, we want to develop a system that is both adaptable and extensible. To put it another way, such a system would help cryptocurrency investors make better decisions while buying and selling cryptocurrency. Using several factors, the study's results have significantly influenced Bitcoin price forecasts. Investment choices are often guided by such analyses for many fund managers and private investors. Scientists have developed a flexible and scalable strategy for determining an appropriate script's ideal value. Investors will need a mechanism to choose which currency to purchase at any given moment according to market circumstances as trading platforms progress.**

***Index Terms*— Machine learning, Crypto currency, PSO, Accuracy, F1 score, recall value, Precision.**

I. INTRODUCTION

Cryptocurrency is a form of virtual currency that is encrypted to prevent forgery and double spending. The networks behind many crypto currencies are completely decentralized. The blockchain technology is crucial to these. Global computer networks keep a general ledger. Digital assets include cryptocurrency. It runs on a decentralized system. Numerous industries, including finance and law, are expected to be shaken up by blockchain and related technology, according to experts. Faster monetary transactions are one of the main advantages of cryptocurrency. The inconsistency of prices and the high cost of transactions are two major constraints. When using cryptography to safeguard digital or virtual money, simplicity in maintaining and managing the cryptographic information is a primary concern. It is facilitating the avoidance of complexity and the reduction of data processing time. Information may be accessed in this system through bitcoin and individuals with certain permissions. Present research is focusing on following objectives:

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1. Estimating cryptocurrency's potential using data from the coin market cap
2. Keeping a tally of crypto assets over the course of a year to determine their best selling price
3. Developing an original method for forecasting optimal or appropriate pricing
4. Easing the burden on the investor by giving them the best possible pricing

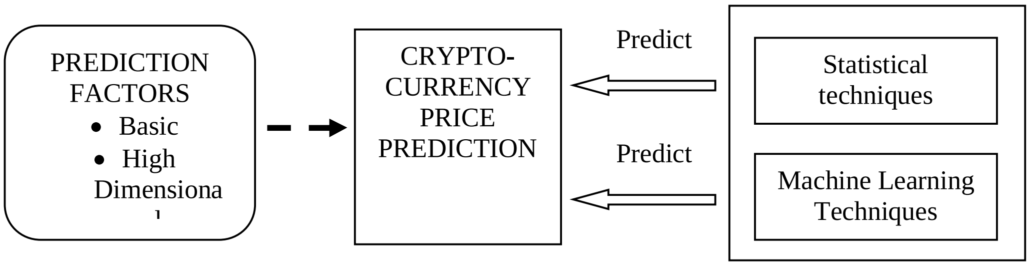


Figure 1. Cryptocurrency Price Prediction using machine learning

A. Machine learning

Understanding and developing 'learning' techniques, or methods that use data to enhance performance on some set of tasks, is the focus of ML, a subfield of computer science. It's considered a kind of AI. In order to generate predictions or judgments without being explicitly programmed, machine learning algorithms construct a model using sample data. This data is referred to as training data. In many fields, including health, email filtering, voice recognition, and computer vision, traditional algorithms would be too time-consuming or costly to design. This is where machine learning algorithms come in.

B. Particle Swarm Optimization

PSO was first suggested by Kennedy and Eberhart in 1995. Scientists that study social behaviour believe that individuals of a travelling school of fish or flock of birds "may profit from the experience of all other members." When one bird in a flock goes out in search of food, the others may benefit from the information it gathers by hearing from the other birds about the best spots to eat. In this context, "best" means "best" in a high-dimensional issue space, where several solutions exist.

C. LSTM

LSTM has been recognized as a prominent artificial RNN. Such is widely used in the field of deep learning. One of LSTM's distinguishing features is its capacity for connectivity and feedback. Contrast with a regular feed forward neural network, which this is not. This goes beyond handling individual pieces of information, like graphics. It's also the last step in a series of media files, such as an audio or video file. To accomplish classification tasks, LSTM networks are deemed appropriate. LSTM networks have been considered as a type of RNN. Aside from the regular units, LSTM also supports some unique ones. A single ‘memory cell' makes up an entire LSTM unit. These memory cells can keep information stored for very long periods of time. Due of LSTM's improved customization options, users are increasingly switching over from RNN. They can control the inflow and distribution of Inputs based on learned Weights. Therefore, it allows for adaptability in output management. Accordingly, LSTM is enabling management skills and productive outcomes.

D. Crypto currency

Cryptocurrency, often known as crypto, crypto-currency, or just crypto, is a kind of digital money meant to function as a means of exchange on a decentralized network, rather than a centralized one backed by a government or a bank. A digital ledger is a database that keeps track of who owns currencies and when. It uses encryption to prevent unauthorized access to the database and ensure the integrity of all transactions and coin ownership transfers. Cryptocurrencies, despite their name, are not regarded to be currencies in the classic sense.

E. Role of Machine Learning in Crypto currency

Predicting cryptocurrency using Machine Learning is the best option available. In order to make a reasonably accurate prediction, the model needed to satisfy a number of criteria. Daily and 5-minute interval price predictions for Bitcoin are made using a wide variety of ML models, including as LDA,LR, RF, XGBoost, SVM, DT, QDA, and KNN. When it comes to blockchain and cryptocurrencies, the uses of machine learning go far beyond price prediction. By streamlining the back-end processes of crypto trading and mining, ML has the potential to address the security problems in this technology through deep learning and reinforcement learning.

II. Literature Review

Various studies have been conducted to determine how to best predict the price of cryptocurrencies. In 2013, A. Cheung [1] received almost little attention from the academic community. As a result, individuals complete their prior knowledge gaps. As part of our research on the occurrence of Bitcoin bubbles, we deploy a newly created tool that is pretty effective at spotting bubbles. There have been a number of brief bubbles in the cryptocurrency market since 2010, but the three largest bubbles all occurred in the years between 2011 and 2013, lasting between six and six-and-a-half months each and ultimately leading to the downfall of Mt Gox. Numerous studies have shown that the hazards associated with Bitcoin may be mitigated. In 2019, GARCH-in-mean models were used by J. Liu [3] to investigate the link between volatility and returns of the dominant cryptocurrency and the ripple effects of the cryptocurrency market. According to E. Bouri [4] in Inn 2020, all three cryptocurrency have had considerable jump activity in their return series. These numbers suggest that the existence of one cryptocurrency boom raises the probability that subsequent cryptocurrency booms will occur as well. Conversely, co-jumping refers to jumping in sync with other traders to maximize volume. In 2020, N. Akbulaev [5] studied the theoretical and practical connections between Bitcoin and Ethereum. Expanding the scope of previous studies on the fundamental properties of Bitcoin and Ethereum and the correlations between their values has allowed for a better understanding of recent trends in the industry. The values of Bitcoin & Ethereum were shown to be correlated, and this connection might be leveraged to mitigate risk when trading cryptocurrencies on exchanges like Gemini. In [6], we looked at whether Bitcoin is a means of exchange or an asset, as well as its present and potential future applications. Their research demonstrates that Bitcoin's statistical properties are distinct from those of conventional asset classes like stocks, bonds, and commodities, and this holds true in both stable and volatile financial environments. Speculation, rather than usage as a means of trade or currency, is the most common use of Bitcoin, according to data collected from Bitcoin accounts. S. Corbet [7] published a study in 2018 that looked at the temporal and frequent connections between three major crypto currencies and many different types of financial assets. [7] Many indicators point to the fact that these possessions are distinct from monetary and material prosperity. The data suggests that Bitcoin investments may provide diversification advantages for short-term traders. The interconnectedness of things may change over time as a result of shocks to the financial system from outside the nation. In 2013, E. Turkedjiev [8] used the ANN to provide short-term stock value predictions, particularly for financial institutions. The nonlinearity of artificial neural networks makes them useful for analyzing stock market time data (ANN). The Hong Kong Straight Train and the QDII, both introduced in 2007, also had a substantial effect on the price gaps between A and H shares in 2010. Several legislative proposals are also made with the goal of narrowing the gap between A- and H-stock prices. According to L. Guoyi [10], the total equity & GDP, earnings after tax per share, & market index are all significant elements that affect a bank's stock price. To determine whether or whether this information has a relationship to the end-of-day share prices of the banks in question, a test model is employed for analysis and verification. According to S.Beng Ho [11], in order to have a good general learning machine, you need one that can solve a broad variety of problems fast in a dynamic environment.

III. Problem Statement

There is an immediate need for a scalable and flexible methodology to estimate the value of cryptocurrencies. The research will take into account the results of previous studies on Deep Learning and Machine Learning. We want to look at the performance and computational expense of a traditional deep learning system. Price predictions for popular cryptocurrencies including Bitcoin, Litecoin, Ethereum, Waves, and BTT should be evaluated, and existing techniques should be compared to those that have been proposed. In order to suggest a new method for predicting the prices of ETH, BTC, LTC, & WAVE cryptocurrencies, research on existing methods and problems in this area is required.

IV. Proposed Work

A. LSTM and Its Training Mechanism

The "net" network that has been trained is saved in the system so that it may be tested again later. Two LSTM layers were used in the implementation, which resulted in a trained network. During the training process, the proposed model makes use of not one, but two LSTM layers before resorting to a drop out layer. Seventy percent of the data set is used for training purposes, while the remaining thirty percent is used for testing. The LSTM-dependent neural network is trained based on the features. Training duration is affected by a number of parameters, one of which is batch size. Accuracy is improving thanks in large part to the hidden layers and dropout layers. Once a dataset is obtained, characteristics are chosen to use in the training process. Then, a 12 hidden layer LSTM1 layer and a 5 hidden layer LSTM2 layer are implemented, with the training/testing ratio determined. Over fitting is fixed by dropout layers, and after that a fully connected layer and a softmax layer are utilized. Decisions on potential intrusions may be made with the use of a classification operation.

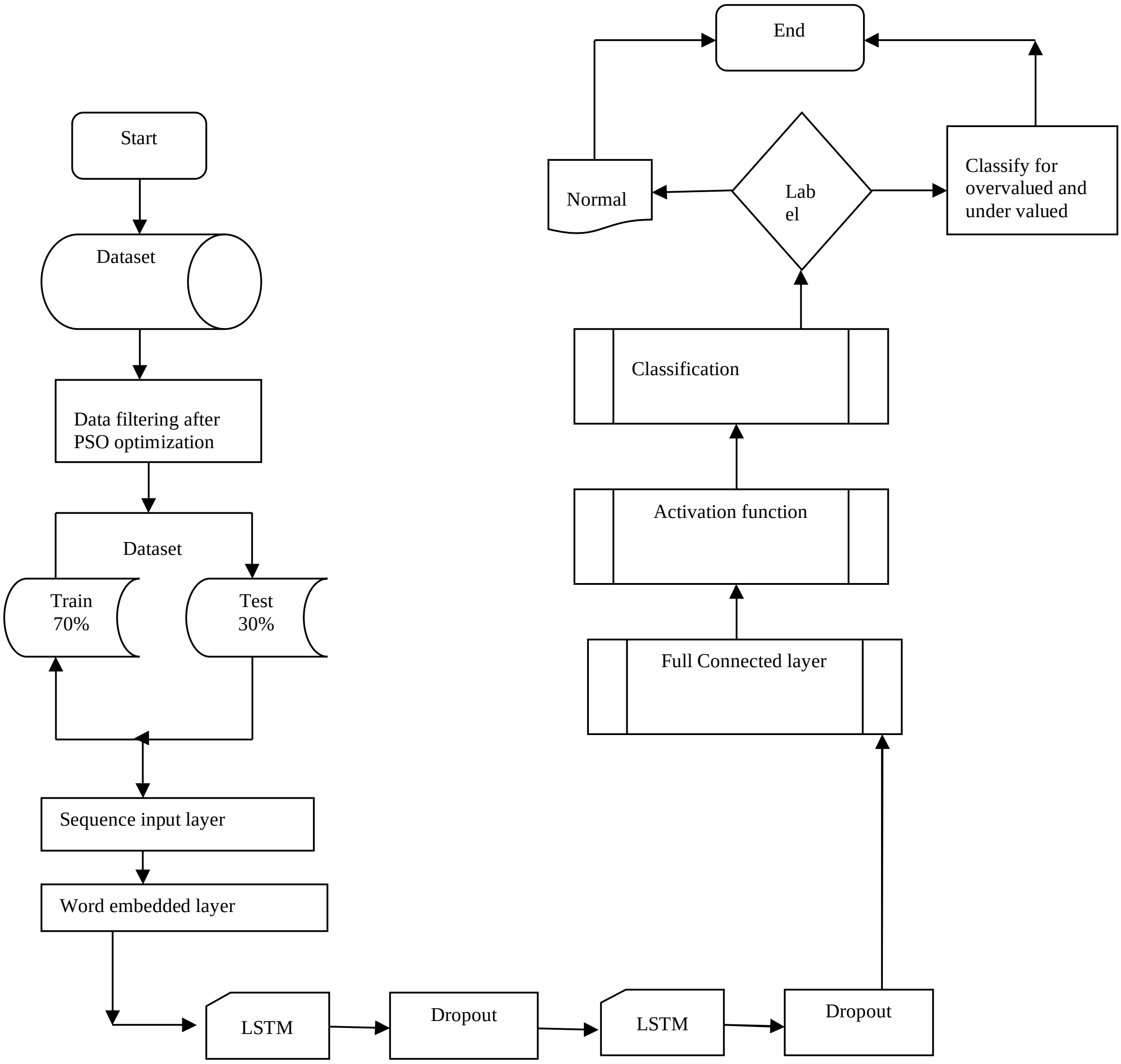


Figure 2. Process flow for proposed work

B. Research Methodology

The dataset of crypto currency are captured using python script and PSO is applied over dataset. The PSO is supporting in getting optimized price in order to support investor regarding best prices. Then dataset is filtered considering optimized value and machine learning approach is used for training.

Proposed objectives include study on the establishment of records of Bitcoin pricing. In the current study, categorization of cryptocurrency prices is recommended on the basis of undervalue, overvalue, and typical pricing. Researchers may now evaluate their findings with the help of the accuracy parameters they obtained.

V. RESULT AND DISCUSSION

Training operation is made after filtering optimized dataset in case of BTC, Etheriam, polygon matic, LTC and wave.

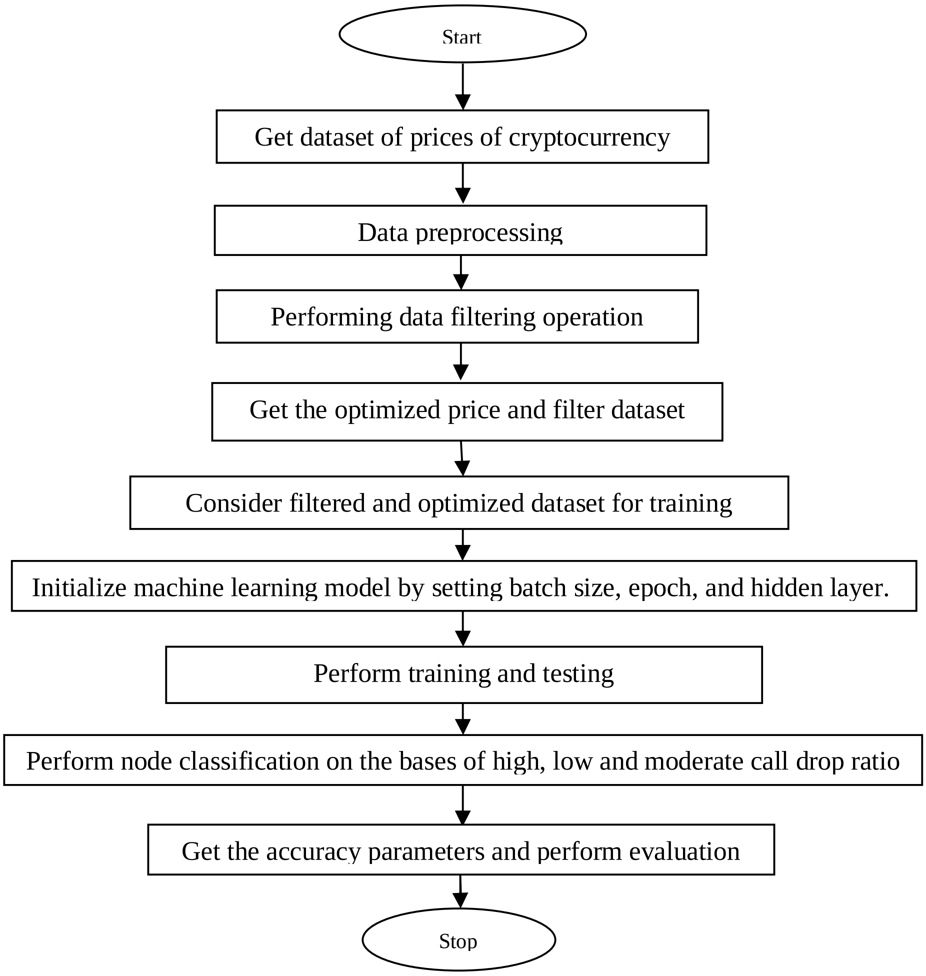
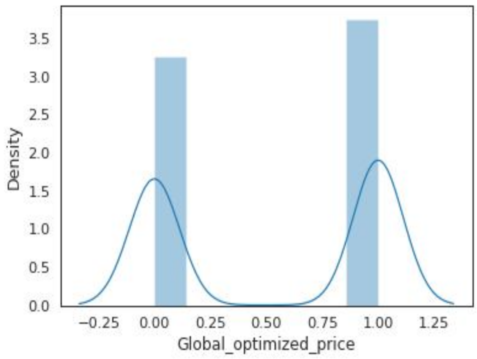


Figure 3. Process flow of proposed work



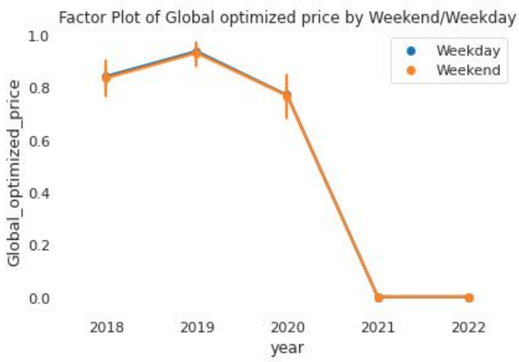


Figure 7. Global optimized price   Figure 8. Factor plot of global optimized price by weekend/weekday

Error and accuracy report after training of LSTM model

- Train Mean Absolute Error: 0.10702336612861828
- Train Root Mean Squared Error: 0.16077715963351358
- Test Mean Absolute Error: 0.022237375378608704
- Test Root Mean Squared Error: 0.022237375378608704
- Train Accuracy: 0.8929766338713817
- Test Accuracy: 0.9777626246213913

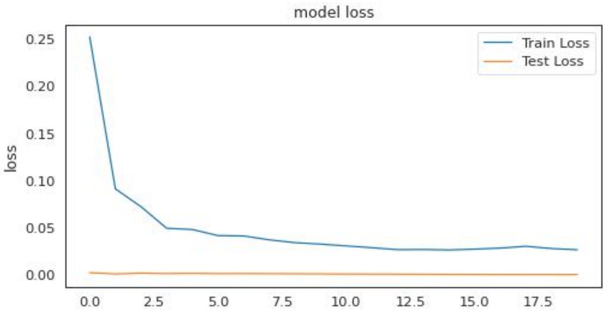


Figure 9. Simulation of training loss and testing loss

TABLE I. ANALYSIS OF ACCURACY OF CRYPTOCURRENCY PRICE PREDICTION

Date	BTC	ETHERIAM	WAVE	LTC	MATIC
10/9/2022	98.5317806	94.4814959	98.0737862	98.6103608	88.4602016
10/10/2022	99.783436	92.6781234	98.0465749	98.2668051	89.6173091
10/11/2022	96.9286016	97.6433739	98.5264403	98.670375	97.0969601
10/12/2022	97.7737	97.2695299	98.3237916	98.451252	99.5937368
10/13/2022	95.92523	96.4562918	98.3094838	98.1136046	99.5400505

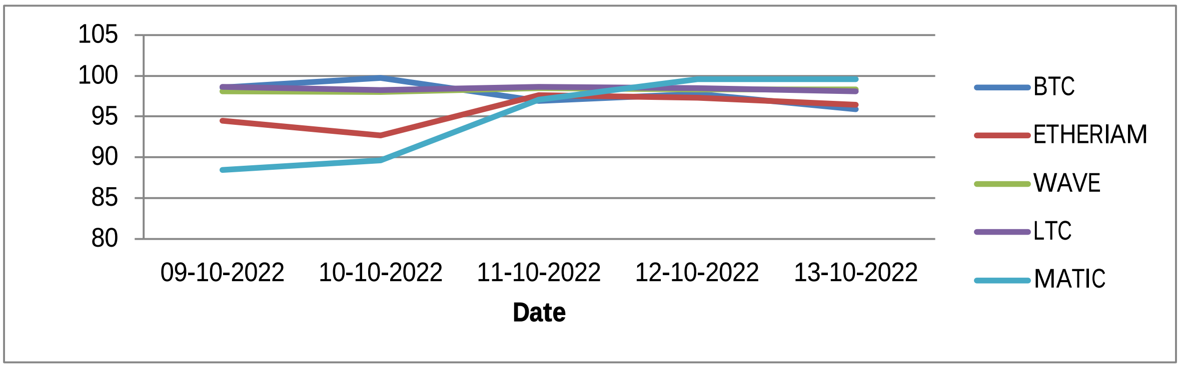


Figure 10. Comparison of accuracy for different cryptocurrency

VI. CONCLUSION

The cryptocurrency industry has developed a complex cryptographic infrastructure to oversee its many operations. The issues that arise from manually handling a crypto currency's administration are addressed and avoided in this project. Information likes as users, crypto holders, author ids, and author biographies are being managed as part of the research. The research sphere is expansive. When handling data, this system took into account a number of factors. The simulation results show that the suggested technique is more precise than previous methods. Simulation results conclude that proposed LSTM model is providing accuracy above 97%.

FUTURE SCOPE

Due to rapid growth in craze of cryptocurrency it has become essential for investors to take investment decision considering overvalue, under value and normal value. Present research has focused on the optimized value of cryptocurrency and proposed efficient machine learning approach. Such research could play significant role in predicting best prices in case of stock market also. Thus present research would contribute toward different investment options.

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