Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 7, No. 4, August, 2023

Using PPO Models to Predict the Value of the BNB Cryptocurrency

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Abstract

This paper identifies hidden patterns between trading volumes and the market value of an asset. Based on open market data, we try to improve the existing corpus of research using new, innovative neural network training methods. Dividing into two independent models, we conducted a comparative analysis between two methods of training Proximal Policy Optimization (PPO) models. The primary difference between the two PPO models is the data. To showcase the drastic differences the PPO model makes in market conditions, one model uses historical data from Binance trading history as a data sample and the trading pair BNB/USDT as a predicted asset. Another model, apart from purely price fluctuations, also draws data on trading volume. That way, we can clearly illustrate what the difference can be if we add additional markers for model training. Using PPO models, the authors conduct a comparative analysis of prediction accuracy, taking the sequence of BNB token values and trading volumes on 15-minute candles as variables. The main research question of this paper is to identify an increase in the accuracy of the PPO model when adding additional variables. The primary research gap that we explore is whether PPO models specifically trained on highly volatile assets can be improved by adding additional markers that are closely linked. In our study, we identified the closest marker, which is a trading volume. The study results show that including additional parameters in the form of trading volume significantly reduces the model's accuracy. The scientific contribution of this research is that it shows in practice that the PPO model does not require additional parameters to form accurately predicting models within the framework of market forecasting.

Keywords:

PPO; BNB;
Cryptocurrency;
Cryptomarkets;
Binance;
Machine Learning;
Neural Network.

Article History:

Received:	14	March	2023
Revised:	29	May	2023
Accepted:	11	June	2023
Available online:	12	July	2023

1- Introduction

When considering the peculiarities of the formation of cryptocurrency markets from the perspective of their neural decomposition (i.e., from the perspective of the possibility to parse their components for analysis by neural networks), it is necessary to understand several interrelated and critical regularities:

- The value and market value of individual cryptocurrencies are determined due to their fundamental technological value;
- Cryptocurrency markets, like classical securities markets, are formed and subject to system-wide market laws;
- Cryptocurrencies exist within their own development paradigm, with little resemblance to the behavior of other market assets.

The author's opinion is that cryptocurrency markets reflect the success of cryptocurrency projects. In practice, cryptocurrency markets are formed under technological pressure, in which market participants determine the prospects of a particular technology using the mechanisms of market competition.

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DOI: http://dx.doi.org/10.28991/ESJ-2023-07-04-012

Both cryptocurrency markets and technical methods of analysis are understudied areas of science. Despite its promise as an applied tool for market analysis, only a few studies have considered this toolkit in the scientific environment. For this reason, the authors try to create a scientific foundation for this issue. In terms of neuromodeling (i.e., bringing the system into a state where we can consider the system using neural networks), the significant problem is that any such toolkit brings the system into a black box state. This, in turn, significantly complicates the understanding of the entire system. The need for this study is dictated by the need to improve the analytical tools for algorithmic trading. The main scientific novelty is the application of PPO models for predicting BNB cryptotokens.

From the viewpoint of the available functionality, market analysis tools can be conditionally divided into two categories: statistical methods and artificial intelligence methods. Statistical methods include the logistic regression model, the ARCH model, etc. Artificial intelligence techniques include multi-layer perceptrons, convolutional neural networks, naive Bayes networks, backpropagation networks, single-layer LSTMs, support vector machines, recurrent neural networks, etc.

The authors of this study propose three hypotheses:

- The application of simple machine learning tools (in this case, the PPO model) on the altcoin market (BNB) should allow for predicting the value dynamics of assets on the cryptocurrency market (in this case, BNB). Achieving positive trading dynamics will confirm this research question;
- The application of additional data sources in the applied models should significantly change the model's accuracy;
- We can assume that the excessive performance of PPO models may indicate that specific algorithms of big players influence the formation of the market for this or that token.

2- Literature Review

In the context of scientific research, the affected subject is practically not covered in scientific works. In the framework of the scientific literature review, the authors have identified two main research blocks:

- Literature sources for the application of artificial intelligence, machine learning, and neural networks as tools for market analysis and predictions;
- Analysis of cryptocurrency markets using machine learning tools.

The foundation of this research is the work devoted not only to the neural analysis of cryptocurrency markets but also to the classical ones because of their similarity. Yun et al. [1] consider the possibility of applying time-dependent characteristics of stock price data over a short data period; they also pioneer best feature subset selection. The proposed algorithm uses two separate input feature sets: internal technical indicators and external market prices. This bilateral forecasting scheme goes through a two-stage feature selection process composed of feature set expansion, hybridized genetic algorithm-machine learning regressions to select important features, and importance score filtering to select optimal features.

Cheng & Wei [2] propose new and innovative hybrid approaches to novel portfolio construction approach that use varying models for stock prediction and portfolio selection. Using their innovative method, the authors quite thoroughly demonstrated that the proposed model-building methods are superior to traditional methods (without stock prediction) and benchmarks in terms of returns and risks. Ding & Qin [3] conducted a comparative analysis where they compared the model with the LSTM network and deep recurrent neural network models. Research indicated a significant increase in the accuracy of the associated model in comparison to the other two models in predicting multiple values simultaneously, and its prediction accuracy is over 95%.

In terms of analyzing cryptocurrency markets exclusively, the primary and most promising studies are those devoted to machine learning tools and neural networks. The most recent studies show high performance. For example, Oviedo-Gómez et al. [4] show that Gaussian Process Regression models allow the best performance metrics through the following predictors: high and low Bitcoin prices, ask-sum, and Bitcoin price lagged. Note that cryptocurrency markets do not obey the usual patterns [5] and follow their own trends and rules [6]. Recent research has also significantly expanded our understanding of modern ML and AI tools. Considering the peculiarities of forecasting cryptocurrency markets, we can note many original forecasting methods based on neural networks and related tools; however, in the context of a broader understanding of neural tools for market modeling, PPO models are a relatively new type [7].

Some studies, such as the one conducted by scientists at the Indian Institute of Technology, have shown the success of models such as linear regression, K-nearest neighbor (KNN), and statistical models such as Auto-ARIMA and Facebook's Prophet (Fbprophet) [8]. Individual scholars consider not only time series prediction tools but also complex multivariate portfolio analysis models [9].

Of particular interest in the evaluation and analysis of cryptocurrency markets is the possibility of using "soft" non-market indicators, for example, data from social networks such as Twitter and Facebook. For instance, Ante Lennart from the Blockchain Research Lab considers the impact of Elon Musk's tweets on market movements. She discovered that, on average, price fluctuations work only in Dogecoin-related Tweets but not for Bitcoin. Considered in isolation, non-negative tweets from Musk lead to significantly positive abnormal Bitcoin returns. Individual tweets do raise the price of Bitcoin by 16.9% or reduce it by almost 11.8% [10]. As for bitcoin prediction, the study "A Stacking Ensemble Deep Learning Model for Bitcoin Price Prediction Using Twitter Comments on Bitcoin" showed impressive results regarding relevant tweets, where the mean absolute error (MAE) reached 88.74% [11].

Studies devoted to Variational Mode Decomposition and BiLSTM are also interesting. A good example is a paper by researchers from the Center for Computational Engineering and Networking. This paper explores a novel technique that establishes a relation between signal processing and volatile stock forecasting methods via variational mode decomposition [12]. Among the studies, in addition to conceptually complex machine learning tools, there are also relatively simple recurrent neural networks with few layers and input data [13, 14]. The studies dedicated to analyzing cryptocurrency markets themselves are nothing new; a significant number of studies are devoted to the possibilities of NN and ML tools, in which only the analyzed tokens are changed [15, 16].

For this reason, the possibility of identifying hidden patterns in related assets is of particular interest. If we consider that predictive models based on artificial intelligence have become the core tool of market analysis [17], then the importance of forming adequate and timely predictive tools becomes obvious. Among the works devoted to market regularities and neuromodeling of time series, there are practically no works devoted to altcoins and BNB, in particular. The only exception is the work "Ensemble of machine learning algorithms for Cryptocurrency investment with different data resampling methods," Institute of Telecommunications of Portugal [18]. The authors considered the possibility of neuromodeling market patterns to predict the behavior of the BNB market.

3- Materials and Methods

As part of the analysis, the work is structured under the following headings: introduction, literature review, materials and methods, results, discussion, and conclusion. In the "Introduction" section, the authors declare the fundamentals of the study and define the conceptual boundaries and hypotheses. In the "literature Review," the authors analyze the theoretical aspects of the study and determine the existing research gap. In "Materials and Methods," the authors demonstrate the original data and the analysis logic. The "Results" section contains output data, graphs, and the final provisions of the analysis conducted. "Discussion" contains discussion materials within which the potential for further research is identified.

The study model can be expressed in the following form (Figure 1).

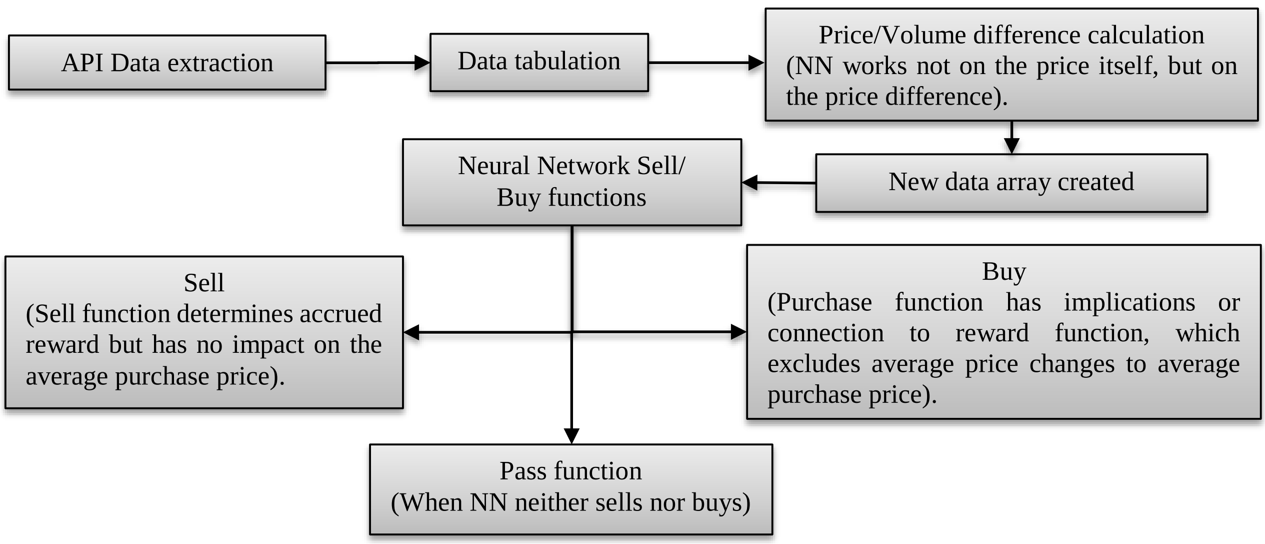

Figure 1. The methodological framework of the study

This research is based on two interrelated parts: the data itself and the model used for training. The main tools for the data analysis are Python 3.9 and the following libraries: NumPy, Pandas, Matplotlib, Math, Random, Time, IPython.core.debugger, Collections, TensorFlow, Wandb, hvPlot, Gym, and Python-binance. The data for model training was obtained from Binance.com through the API embedded in its services. The authors defined the trading pair BNB/USDT as the object of their study.

Data sampling considered the dynamics over the last 150 days. The main difference between this research and the already available scientific works is that the analysis is based on the simplest possible prediction of time series using PPO models.

PPO is a qualitative improvement in the widely used DQN model. The DQN (Deep Q-Network) algorithm was developed by DeepMind in 2015 [19]. It could solve a wide range of Atari games (some to a superhuman level) by combining reinforcement learning and deep neural networks at scale. The algorithm was developed by enhancing a classic RL algorithm called Q-Learning with deep neural networks and a technique called experience replay.

PPO is a policy gradient method and can be used for environments with either discrete or continuous action spaces. It trains stochastic policies in an on-policy way. Also, it uses the actor-critic method. The actor maps the observation to action, and the critic gives an expectation of the rewards the agent will receive for the observation given. As part of the neural network development, the following research model was used (Figure 2).

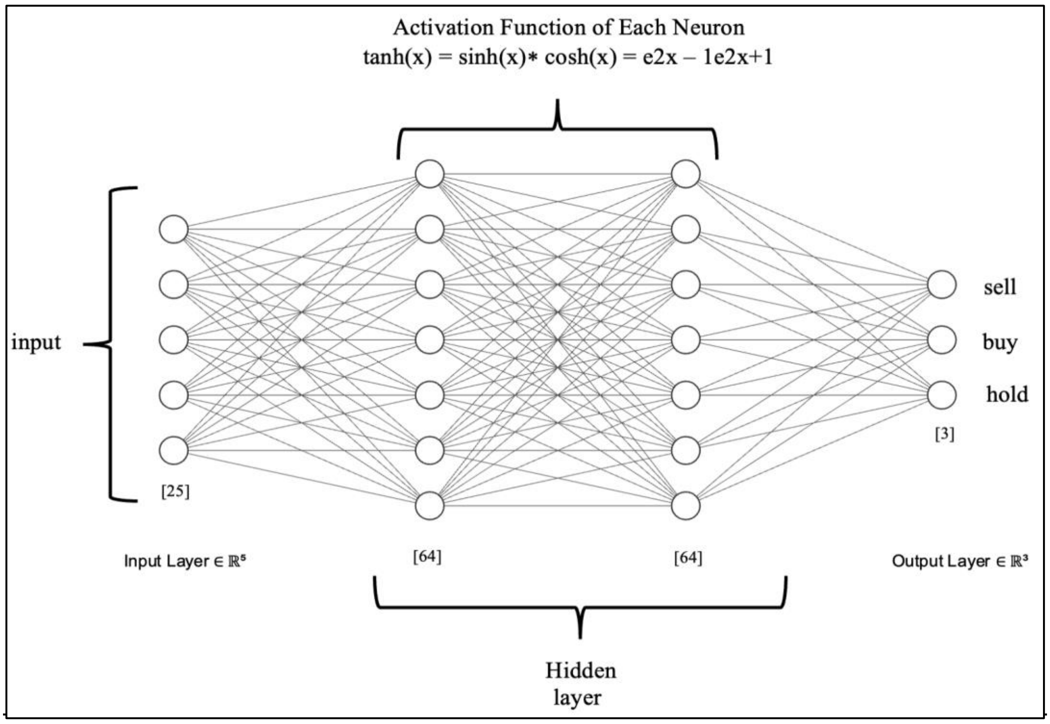

Figure 2. The neural network models

At the early stage of its evolutionary path, the PPO model was assumed to create an algorithm with the efficiency and reliability of TRPO models under first-order optimization conditions. For this reason, this model can be expressed as follows: $r_t(\theta)$determine the probability ratio

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \tag{1}$$

Thus, we obtain $r(\theta_{old})$

$$r(\theta_{old}) = 1 \tag{2}$$

TRPO's borrowed qualitative characteristics allow us to maximize the desired "goal":

$$L^{CPI}(\theta) = \hat{\mathrm{E}}_t\left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}\hat{\mathrm{A}}_t\right] = \hat{\mathrm{E}}_t\left[r_t(\theta)\hat{\mathrm{A}}_t\right] \tag{3}$$

where *CPI* is the minimum changeable value of the function.

Without$L^{CPI}$the generated model will suffer from the excessively high volatility of the correction. Thus, the PPO model will correct the reward in case of an excessively high level of deviation $r(\theta_{old}) = 1$ from 1. Thus, the model can be represented as follows [15]:

$$J^{CLIP}(\theta) = \hat{\mathrm{E}}_t\left[\min\left(r_t(\theta)\hat{\mathrm{A}}_t, clip(r_t(\theta), 1-\varepsilon, 1+\varepsilon)\hat{\mathrm{A}}_t\right)\right] \tag{4}$$

where ε is a hyperparameter of the model.

Since there is no model modification in the case of changes in the input data, the presented function has a finite form. Simultaneously, the training itself was performed on randomly mixed data sets to exclude the linear remembering by the neural network of ascending and descending patterns. The analyzed BNB token is one of the most promising tokens, whose fundamental value is determined by its role in the broader Binance ecosystem, within which it acts as a commission tool (Figure 3).

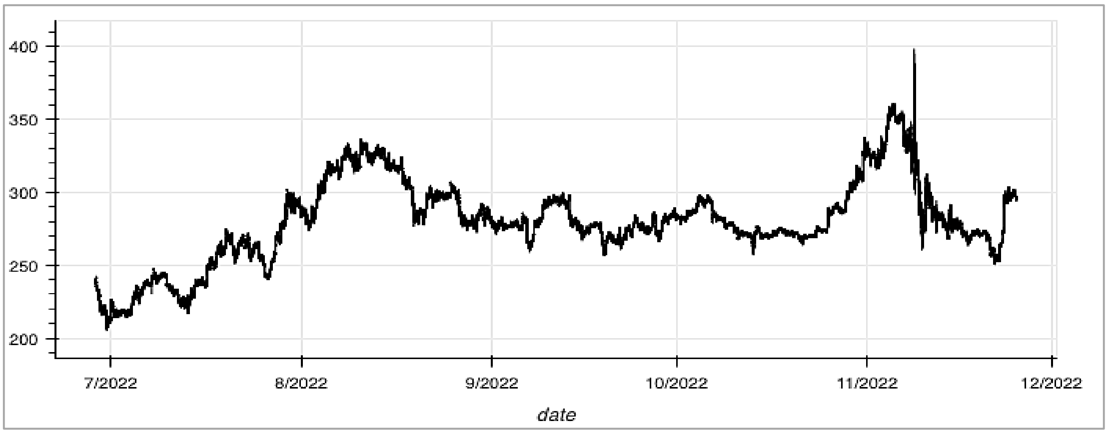

Figure 3. BNB price fluctuations (generated by bokeh)

In the context of its price dynamics, the token is characterized by high volatility. The basis of the study is 15-minute tickers, within which data on the price and trading volumes at the time of ticker formation were obtained through the API. Table 1 presents the data sample.

Table 1. Data sampling for neural network training

	Open	High	Low	Close	Volume
Count	14400.000000	14400.000000	14400.000000	14400.000000	14400.000000
Mean	279.993938	280.659431	279.305472	279.992778	5069.083734
std	28.197477	28.335737	28.084528	28.197391	7106.043676
min	206.000000	207.500000	205.400000	206.000000	265.227000
25%	268.900000	269.400000	268.300000	268.900000	2064.438750
50%	278.200000	278.800000	277.600000	278.200000	3343.778000
75%	295.000000	295.700000	294.300000	295.000000	5672.177750
max	387.700000	398.300000	375.600000	387.900000	254265.682000

A total of 14,400 data parameters were generated, each representing a discrete, bite-sized array of data. Many neural networks, especially in the field of time series prediction, suffer from improperly mixed data, due to which they are often trained to predict time series in bull or bear markets only.

4- Results

4-1- PPO without Volume

The results of the study are the following chart (Figure 4), which shows the profit/loss of each generation of model training.

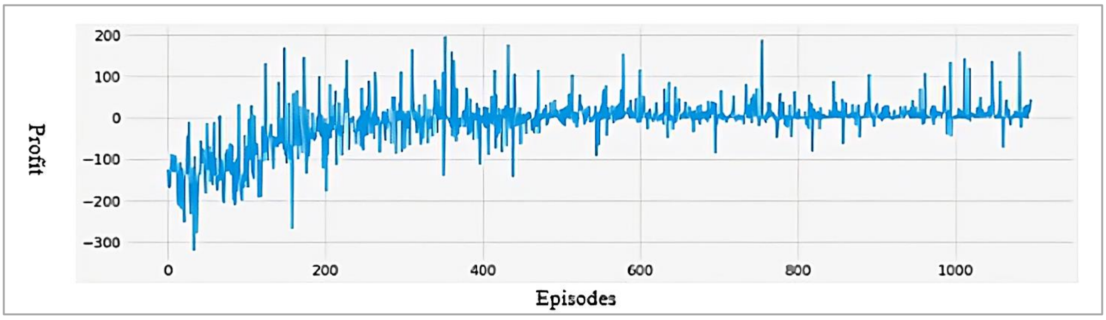

Figure 4. PPO profit/loss (generated by bokeh)

As can be seen, the first few hundred generations trade in a big minus; however, by the 250th generation, the model goes into relative equilibrium. We can observe an interesting pattern: the model in question has a high level of volatility within the trading strategy. It aggressively trades both uptrends and downtrends, due to which it succeeds in generating both high profits and losses.

4-2- PPO with Volume

In contrast to the first PPO model with the volume of trades, the model has a high level of instability, and by the five hundredth generation, it comes to a very stable rate of profitability, and in the case of anticipated losses, it significantly reduces the rates and volumes of trade. In the context of initially put forward theories, we can note that the application of simple machine learning tools, in this case, the PPO model, in the altcoin market (BNB) allows us to predict the value dynamics of assets quite accurately, as evidenced by the achievement of positive trading dynamics in both models. Note that using additional data sources did not give the actual result. In practice, the use of an additional parameter (trading volume) not only did not increase the accuracy of the model but also led to the "fading" of the neural network activity (Figure 5).

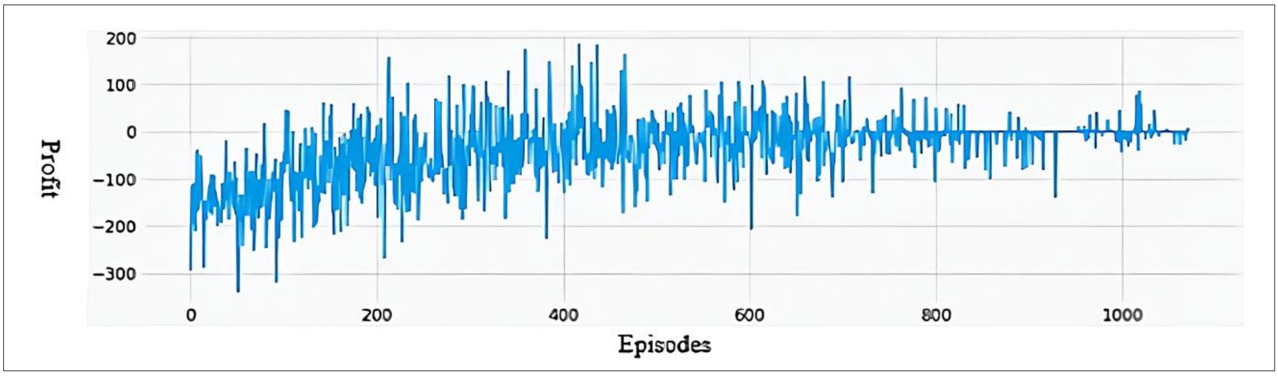

Figure 5. PPO profit/loss (generated by bokeh)

5- Discussion

The authors declare as the main results of the study the practical results of building a model by which it is possible to predict changes in the time series of the value of cryptocurrencies. Although cryptoassets themselves have no fundamental value, their growing popularity requires us to understand market patterns. It is also worth noting that the results obtained by the authors are proof that cryptocurrency markets are significantly influenced by the algorithms of external actors. In other words, price dynamics are subject to a non-market pricing device. That is, the neural network could reach the calculation of the conditional trading model of market makers.

Considering the presented study in the context of the available scientific literature, we can find similar studies applying other models to predict the cryptocurrency market. In the context of applying PPO models, there are not many studies and results to date in addition to our presented research. In the context of technically and conceptually similar studies, we can observe a high degree of variability, especially from a methodological point of view. Considering neural networks as a starting point in a comparative analysis, the most interesting and outstanding works are those of Patrick Jaquart et al. [20] and Oyewola et al. [21].

The peculiarity of the work done by Patrick Jaquart is that all models are trained on the binary classification problem of predicting whether a single coin will outperform the cross-sectional median of returns on the subsequent day, based solely on price information from the previous 90 days. In the context of our study, such a formulation of the question can significantly simplify the model learning process. David et al. [21] present an innovative hybrid walk-forward ensemble optimization method. Additionally, the authors consider a much larger dataset, which includes about 15 trading pairs, each of which then undergoes cross-validation. From the viewpoint of innovativeness, a similar study is also by Ghosh et al. [22]. The authors analyze the price dynamics of NFT and DeFi projects and conduct a mapping using the ISOMAP methodology. ISOMAP resembles a nonlinear feature engineering methodology that is primarily used for dimension reduction and feature transformation. It extends the rudimentary multidimensional scaling (MDS) methodology by preserving the intrinsic geometry of the underlying feature set by estimating the geodesic manifold distances between all pairs of data points. ISOMAP can effectively be used for feature engineering to fetch an optimized representational form in each dimension. As such, their research shows a significant level of accuracy, especially in comparison to classical statistical methods of analysis. From a feature set viewpoint, our study can see significant improvement by means of improving the used dataset and closely related features and indicators. Parvini et al. [23] show how dimensionally different indicators can improve model accuracy.

5-1- Implications and Explanation of Findings

The presented results show that PPO models can be successfully applied to build trading strategies in cryptocurrency markets. The PPO model, based solely on price data with a high level of profitability, is particularly noteworthy. The study results and the fact that the purely price-based model shows much more stable results are due to the specifics of the PPO models, which are mainly focused on working with monogenic data samples. In practice, PPO models do not have the necessary internal tools to handle heterogeneous data.

5-2- Strengths and Limitations

The main limitation of the study is the study parameters set by the authors. The original objective of the study was to demonstrate the possibility of using PPO models in market prediction. However, in terms of the actual application of these models as algorithmic trading tools, there are many potential problems associated, primarily with data availability and the correct timing of transactions. It is also worth noting that the study's strength is the results presented, which show the success of applying simple samples to predict the value of cryptocurrency assets.

5-3- Recommendation and Future Direction

The main direction of further research is the creation of a multilevel system of neural networks, which will be based not on primary stock data but on secondary social index factors. In other words, the main direction of developing neuro instrument development is tools based not on the value of an asset itself but on social indices and tools for their nowcasting.

In the context of the ongoing analysis, the considered models are characterized by a high level of profitability. The study result is achieved, and the built models generate stable growth rates. Comparing PPO models, we can observe the much more significant efficiency of PPO models with simple time series prices. This may seem strange, partly because multifactor neural models should improve their accuracy by introducing new data sources, but in the case of PPO, its strengths are revealed when predicting regular and homogeneous time series.

Simultaneously, it is worth pointing out that the ongoing research has significant applied value. In practice, we see a wide range of applications for relatively simple neural modeling tools for market distribution.

In the context of the obtained results, it is worth noting that the models under consideration and the conditions of their functioning have significant limitations, which partly impose on us specific difficulties in the comparative analysis of individual studies and models. An essential part of the set parameters depends not on the developers but on the model's internal state. It is also worth noting that the presented developments can be applied in the interests of large investment funds to optimize trading strategies in algorithmic trading and banking structures to form anti-crisis prediction tools.

6- Conclusions

In the context of the ongoing analysis, the considered models are characterized by a high level of profitability. The study result is achieved, and the built models generate stable growth rates. Comparing PPO models, we can observe the much more significant efficiency of PPO models with simple time series prices. This may seem strange, partly because multifactor neural models should improve their accuracy by introducing new data sources, but in the case of PPO, its strengths are revealed when predicting regular and homogeneous time series.

Simultaneously, it is worth pointing out that the ongoing research has significant real-life value. In practice, we see a wide range of applications for relatively simple neural modeling tools for market distribution.

As stated in our introductions, we identified a primary research gap in a way that allows us to systematically illustrate whether PPO models can be improved, especially in market conditions where it is difficult to find statistically significant correlations. By adding additional training markers that are closely related to price but do not necessarily mirror it, we can find interesting codependencies between the two. As we used trading volume as a secondary training marker, we can decisively state that it does not improve the PPO model's accuracy. It is also noteworthy that future research should emphasize the usage of other neural network building techniques, especially LSTM-based models, as they show greater potential.

In the context of the obtained results, it is worth noting that the models under consideration and the conditions of their functioning have significant limitations, which partly impose on us specific difficulties in the comparative analysis of individual studies and models. An essential part of the set parameters depends not on the developers but on the model's internal state. It is also worth noting that the presented developments can be applied in the interests of large investment funds to optimize trading strategies in algorithmic trading and banking structures to form anti-crisis prediction tools.

7- Declarations

7-1- Author Contributions

Conceptualization, S.N.S.; methodology, S.N.S.; software, D.V.F.; validation, S.N.S., N.V.K., and E.V.Z.; formal analysis, N.V.K.; investigation, S.A.P. and E.V.Z.; resources, D.V.F.; data curation, S.N.S.; writing—original draft preparation, S.A.P. and E.V.Z.; writing—review and editing, S.N.S. and N.V.K.; visualization, D.V.F.; supervision, S.N.S.; project administration, S.N.S.; funding acquisition, N.V.K. and E.V.Z. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available in the article.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the author.

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