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# Leveragıng On Contınual Machıne Learnıng For Real Tıme Tradıng In Fınancıal Markets

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***Abstract***— In this research paper, a novel neural-inspired approach called the Neuronal Auditory Machine Intelligence (NeuroAMI) is proposed for prediction of cryptocurrency prices - the ripple (XRP/USD) trading pair. The NeuroAMI is implemented as part of a LUNO API systems app and real-time data is generated and captured. Comparisons were also made with two other methods used in cryptocurrency trading called the Non-linear Auto-Regressive Neural Network (NARX-net) and progressive Long Short-Term Memory (LSTM). The experimental results considering the 40%, 60%, and 80% input training level and the Mean Absolute Percentage Error (MAPE) evaluation metric were reported for the considered techniques. From the experimental results, it was clearly seen that on average, the NeuroAMI will outperform the NARXnet and LSTM techniques at the various input training data levels. In addition, it was observed that the proposed NeuroAMI technique attains consistent MAPE error estimates for a given percentage input training level.
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***Keywords :*** *Blockchain, cryptocurrency price, machine learning, neural network, prediction.*

## 1. Introduction

Financial markets play a crucial and impactful role in the development of everyday society as market commodities or financial assets have to be bought and sold at competitive rates in order to meet the needs of a potential number of successful traders from a larger trader pool. This results in a potential huge set of minute-by-minute, hourly, and daily financial transactions and in turn corresponding profits or losses.

In the context of cryptocurrency trading, the profits and losses results in bullish and bearish markets which is a direct consequence of the greed (or fear) index. Thus, it becomes a matter of urgency for cryptocurrency experts and enthusiasts alike to develop as well as support the development of techniques and tools that will guide the trader in making profitable high-yield financial decisions and hence minimize if not eliminate the losses or risks associated with bad market choices or decisions.

In this paper, we develop an effective AI-based technique that is neural-based and can lead to potential profitable transactions in the FOREX or CRYPTEX markets. This technique is inspired by the intelligent operations that occur in mammalian auditory cortex and follows from an earlier study proposed in (Osegi, 2021, Osegi 2023).

## 2. Related Studies

The studies in the field of cryptocurrencies is an active one in which a great deal of research in the use of neural machine learning has been investigated. For instance, Shintate & Pichl (Shintate & Pichl, 2019) used the deep Long Short-Term Memory (LSTM) optimized learning method coined the Random Sampling Method (RSM) for the task of trend prediction classification of the cryptocurrency time series (bitcoin) OHLC dataset obtained from the OkCoin exchange market. In Miura et al (2019), a combination of several ML methods for Return Volatility (RV) prediction of bitcoin data time series was proposed. These methods include the standard MLP, LSTM, Gated Recurrent Unit (GRU), Convolution Neural Network (CNN), Support Vector Machine (SVM), and Ridge Regression (RR) were applied to the analysis of cryptocurrency data.

Dutta et al (2020) proposed a holistic approach to bitcoin price prediction including both endogenous and exogenous variables. They used the Gated Recurrent Unit (GRU), a deep learning extension of the LSTM technique with a simpler and compact architecture for making recurrent price predictions.
Anghel (2020) used TA and ML trading rules in the context of multi-hypothesis testing for evaluating the excess return of crypto assets. Several ML techniques including the Support Vector Machine (SVM), Logistic Regression (LR), Random Forests (RF), Recurrent Neural Networks (RNN), and Wide and Deep Neural Networks (WDNN) were encoded as trading rules trained by a set of 84 features. Omane-Adjepong et al (Omane-Adjepong et al., 2020) explored the chaotic patterns exhibited by some leading BRICS asset cryptos. Five key analytic solution techniques including wavelet time scale decomposition and four testing operations – the Block-Dechert-Scheinlman (BDS), Teräsvirta Neural Network (TNN), Entropy Test for Non-Linearity (ETN), and the Largest Lyapunov Exponent (LLE) tests were proposed. They identified high-level chaos in log-return for intra-week (daily) scale samples of the considered crypto markets. Also, the Non-linear Auto-regressive Neural Network (NARX-net) as a predictor has been used in (Houssein et al., 2020) for the prediction of the Egyptian stock exchange market.
While very good results are obtained for the techniques employed in the aforementioned research studies, it is common knowledge that these techniques require high number of features before a reliable prediction can be made. They also frequently require an extra computation to determine right set of features (referred to as feature engineering problem). In addition, these techniques lack continual learning ability inspired by biological neuronal processing.
Thus, the purpose of this research study is to leverage on emerging continual learning approach for cryptocurrency price predictions.

## 3. Materials and Methods

The materials are composed of input and output documents derived from the LUNO trading view while the specific methods adopted are AI-inspired and based on auditory machine intelligence introduced earlier introduced in (Osegi & Anireh, 2019).

### 3.1. Input and Output Documents

The proposed input and output documents are composed of digitized computer data in the form of prices of crypto or fiat-based currencies. Instances of these data are captured in the form of a flat file open source price dataset for the fiat (forex data) pair and a real-time crypto price pair data.
The output documents are generated by a computer program based on a neural auditory-inspired machine intelligence technique. It uses the last (or past) traded price to make a future prediction of the crypto pair (see sample snapshot in Figure 1).

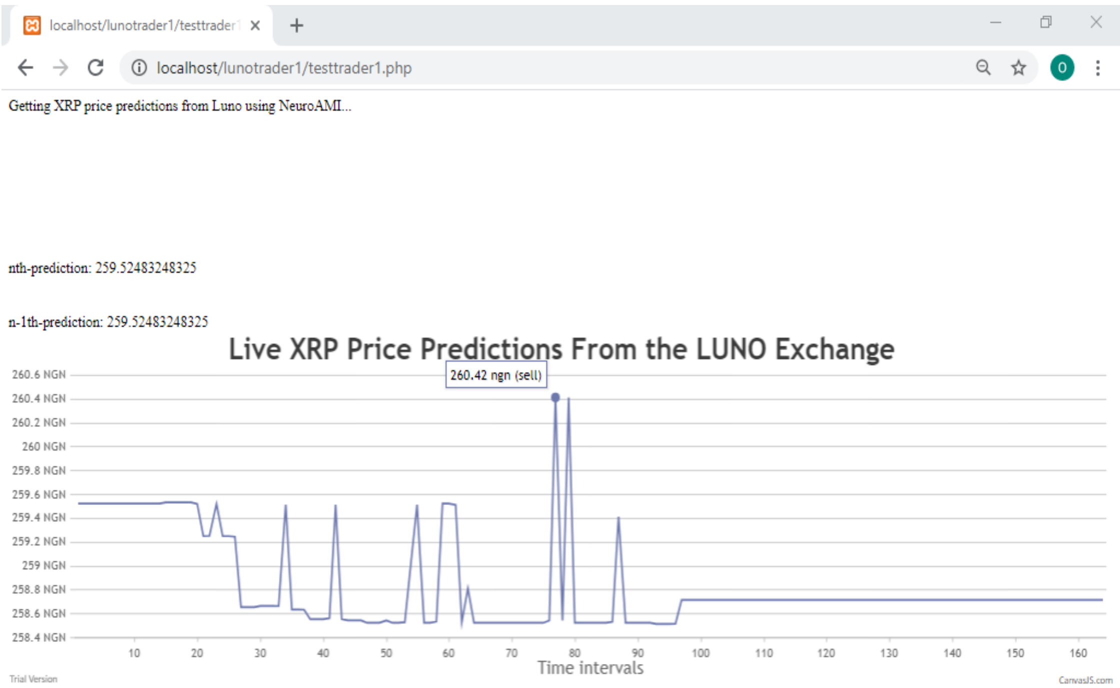


**Figure 1.** A sample snapshot of an output document generated by the neural computer program.

The input documents comprise the last 100 traded prices from the LUNO order book (see sample snapshot in Figure 2).


**Figure 2.** A Sample snapshot of an input document used for real-time analysis.

## 3.2. Artificial Intelligence (AI) Method

The AI method employed is based on an earlier study by first author (Osegi, 2021). This method is called Neuronal Auditory Machine Intelligence (NeuroAMI) and the neuron architecture is shown in Figure 3.

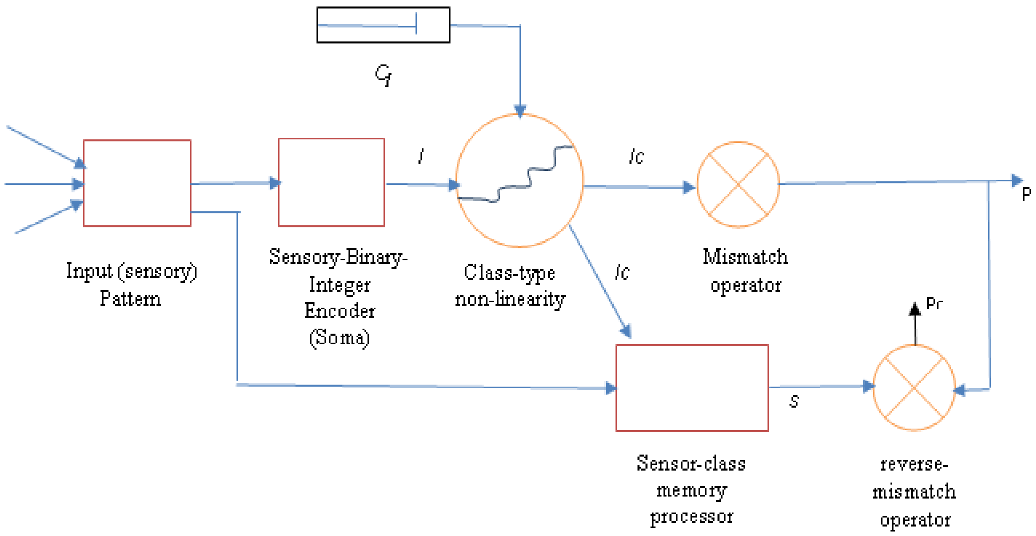


**Figure 3.** NeuroAMI Architecture.

As can be seen from Figure 3, input sensory patterns are fed to both a Sensory-Binary-to-Integer Encoder (SBIE) and a Sensory-Class Memory Processor (SCMP); also, the somatic inputs from the SBIE are parsed to the SCMP via a class-type non-linearity resulting in Integer class-type coding ($I_c$). This allows the formation of sensory memory cells ($s$), and hence the predicted cell ($P_r$) is formed via reverse mismatch operations. Also, mismatch operations enable change detections via the $I_c$ leading to the output prediction state ($P$). To ensure that learning is effectively accomplished and to enforce sparse activations, a frequency class signal level is applied to the non-linearity (Osegi, 2023).

With this neuron architecture, it becomes more advantageous to deal with streaming inputs that change through time using sparse detection. This process is further enhanced using a reinforcement learning process as described in the following sub-sections.

### 3.2.1. *NeuroAMI Learning Procedure*

In the first instance, NeuroAMI learns a sequence of data points (values) automatically/temporally in an adaptive manner such that a mean deviant point is computed as in (1):

$$S_{dev(mean)} = \frac{\left(\left(\frac{\sum [S_{dev}]}{(n-1)}\right) + S_{deviant}\right) - 2}{n+1} \tag{1}$$

where,

$n$ = number of data points in a temporal sequence

$S_{deviant}$ = the *(n-1)*$^{th}$ value of the temporal sequence

$S_{dev}$ = the difference between $S_{deviant}$ and $S_{stars}$

$S_{stars}$ = the *(n-2)*$^{th}$ values of the temporal sequence

$S^*$ = sparse set of input sequences

In order to make a prediction with the NeuroAMI, the formula in (2) is used as follows:

$$S_{pred} = S_{deviant} + S_{dev(mean)} \tag{2}$$

where,

$$S_{deviant} = S_n^* - 1 \tag{3}$$

$$S_{stars} = S_n^* - 2 \tag{4}$$

**Algorithm 1.** NeuroAMI Processing Algorithm

*A.* i: Initialize $S_{pred}$, as prediction parameter, $S_{stars}$, as input sequences (standards) state, $S_{dev(mean)}$ as deviant mean, $j$ as iteration counter.
*B.* ii: *for* all s $\in$ *s.*$S_{stars}$, &&$j$> 1, do
*C.* iii: Compute $S_{deviant}$and $S_{stars}$ using equations (3) and (4)
*D.* iv: $S_{dev} \leftarrow \left\| S_{deviant} - S_{stars} \right\|$ // deviations from standards
*E.* v: Compute $S_{dev(mean)}$ using equation (3)
*F.* vi: Compute $S_{pred}$ using equations (2)
*G.* vii: Update $S_{dev(mean)}$ using Algorithm 2
*H.* viii: *end for*

The update routine in Algorithm 1 describes a learning process following Hebbian-style reinforcement as depicted in Algorithm 2:

**Algorithm 2.** NeuroAMI Learning Algorithm

*İ.* i: Initialize $S_{pred}$, as prediction parameter, $S_{stars}$, as input sequences (standards) state, $S_{dev(mean)}$ as
*J.* deviant mean, $S_{diff(1)}$ as difference between $S_{pred}$,$S_{deviant}$+1and $S_{diff(2)}$ as difference between
*K.* $S_{dev(mean)}$ and $|S_{diff(1)}|$, $l_p$ as correction factor or bias.
*L.* ii: *for* all s $\in$ *s.*$S_{stars}$do
*M.* iii: if $S_{diff(2)} > 0$
*N.* iv: $S_{dev(mean)} \leftarrow S_{dev(mean)} - \left| S_{diff(1)} \right|$ // Weaken deviant mean by a factor, $|S_{diff(1)}|$
*O.* v: elseif $S_{diff(2)} < 0$
*P.* vi: $S_{dev(mean)} \leftarrow S_{dev(mean)} + \left| S_{diff(1)} \right|$ // Reinforce deviant mean by a factor, $|S_{diff(1)}|$
*Q.* vii: else
*R.* viii: $S_{dev(mean)} \leftarrow S_{dev(mean)} + l_p$
*S.* ix: end if

The learning rule is explained as follows:

If the current prediction error of the NeuroAMI neuron is greater than or lower than zero, we reinforce its prediction by decreasing or increasing its deviant weight value by the absolute prediction error difference at the current time step; otherwise, we perform zero or negligible positive reinforcement by adding a very small value (deviant-laplacian correction). In situations where exact matches occur, a small laplacian correction value (typically in small fractions of about a hundredth), is used for deviant weight updates. It is important to emphasize that the learning process in Algorithm 2 may be weakened by a divisive penalty, and strenghtened by a multiplicative penalty.

### 3.3. System Architecture

The system-level architecture captures the core operational modules that used to implement a cryptocurrency trading solution. This architecture is shown in Figure 4.

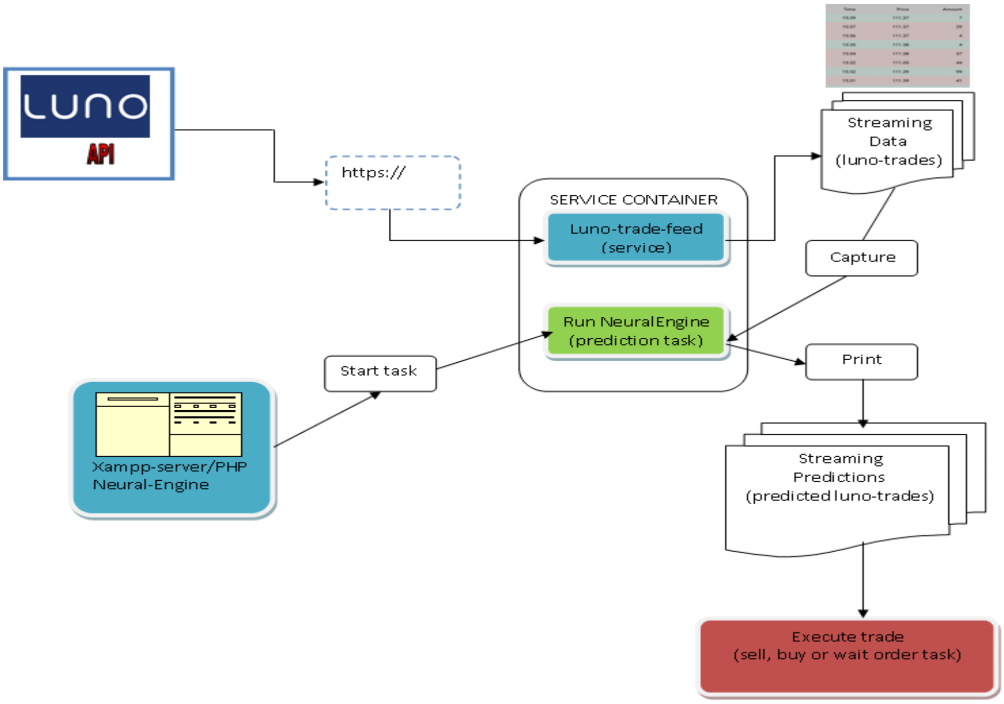


**Figure 4.** Proposed System Architecture of Crypto Trading System (Osegi, 2021).

Considering this architecture, the data processing should be done in near real-time. The key parts of this architecture are the "Luno-trade-feed" and the "Run NeuralEngine" modules. The Luno-trade-feed generates real-time streaming data; thus, data is generated in an online or continual manner. The Run NeuralEngine performs the task of prediction by capturing past streaming data and generating a precise estimate of the last traded price in the next time step. This function has to be done continuously; thus, algorithms that are online-capable are favored. In this research, the auditory-inspired neural technique described in Section 3.2 is proposed as a candidate neural approach.

## 4. Results and Discussions

Real-time experiments are conducted for one of the major cryptos used in the blockchain space; in this case, the XRP coin. In particular, prediction results are reported for the XRPNGN currency pair for 100 samples of intraday trades – the trades representing the orders (sell or buy orders) performed within a specific duration and generated using a NeuroAMI web-based AI software tool in PHP.

In Figure 5, a typical graphical prediction response is shown at run-time. The input Reinforcement Learning Interval (RLI) parameter and sell order threshold values are specified before a prediction run i.e. by clicking the submit button.

When there is an increase, the AI bot will initiate a sell order (see sell caption at about 70th data point); otherwise, a buy decision is initiated. The sell or buy decisions are determined by the NeuroAMI n-th prediction following the last traded price.

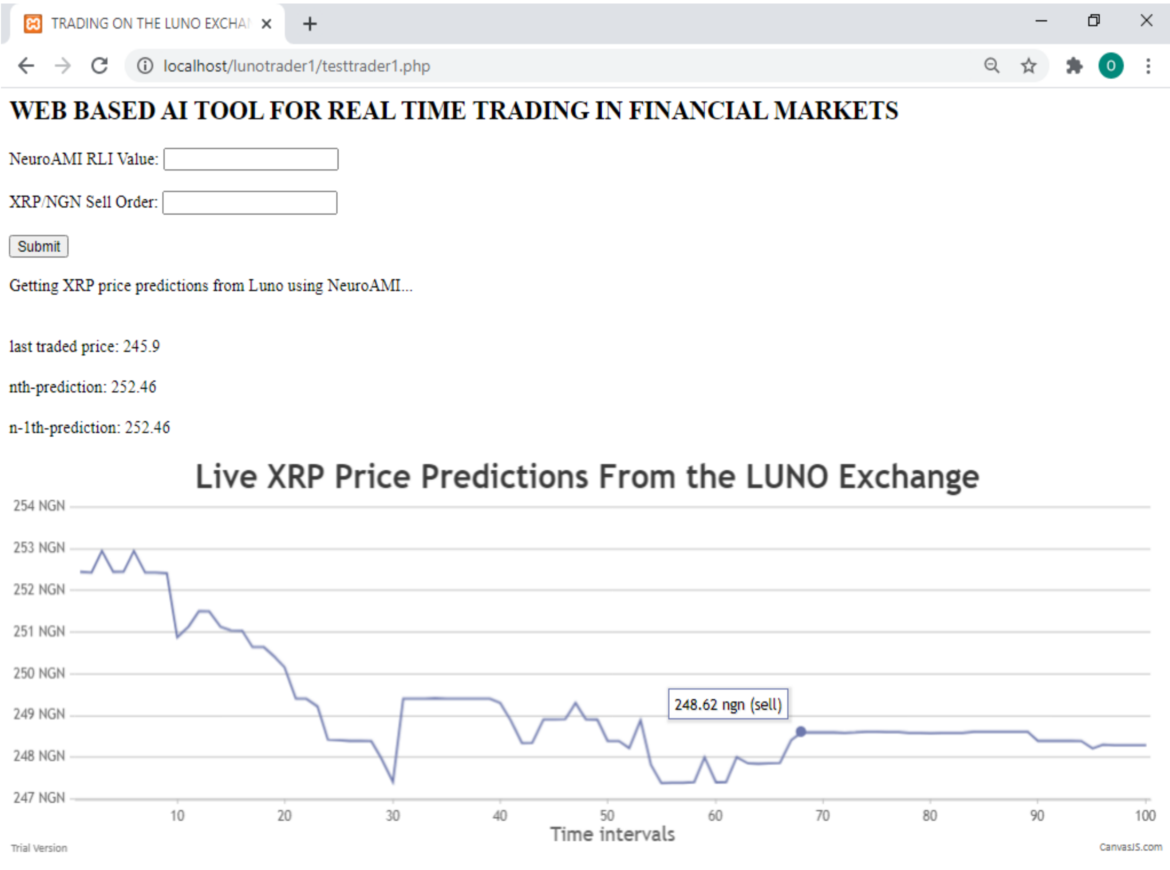


**Figure 5.** Prediction response of the NeuroAMI predictor showing sell-order execution

For the comparative simulation experiments, the input data is sampled continually and fed to the NeuroAMI at 40%, 60%, and 80% levels. The default operating parameters are used for NARXnet (Houssein, 2020) and in LSTM as reported in (Fayek, 2017).

In Tables 1 to 3, the comparative performance of NeuroAMi and NARXnet are presented in terms of the Mean Absolute Percentage Error (MAPE) which is a better performance metric than the Root Mean Squared Error (RMSE) or other statistical metrics for continual learning AI systems (Cui et al., 2016). Also, a comparison with a variant of the Long Short-Term Memory (LSTM) with progressive (continual) learning feature proposed in (Fayek, 2017) is equally reported in Tables 1 to 3.

**Table.1.** Comparative results using real-time XRP trading data (40% level); training data in curly brackets.

| Trial number | NeuroAMI $_{MAPE\{40\%\}}$ | NARXnet$_{MAPE\{40\%\}}$ | LSTM$_{MAPE\{40\%\}}$ |
|---|---|---|---|
| 1 | 0.2422 | 0.8871 | 1.9444 |
| 2 | 0.2422 | 0.4516 | 1.9365 |
| 3 | 0.2422 | 0.4032 | 2.0311 |
| 4 | 0.2422 | 0.7016 | 1.9281 |
| 5 | 0.2422 | 0.8871 | 1.8937 |
| **Mean:** | 0.2422 | 0.6661 | 1.9468 |

**Table.2.** Comparative results using real-time XRP trading data (60% level); training data in curly brackets.

| Trial number | NeuroAMI $_{MAPE\{60\%\}}$ | NARXnet$_{MAPE\{60\%\}}$ | LSTM$_{MAPE\{60\%\}}$ |
|---|---|---|---|
| 1 | 0.2344 | 0.7952 | 1.7384 |
| 2 | 0.2344 | 0.7952 | 1.8346 |
| 3 | 0.2344 | 0.6988 | 1.9067 |
| 4 | 0.2344 | 0.5783 | 1.6015 |
| 5 | 0.2344 | 0.6145 | 1.8358 |
| **Mean:** | 0.2344 | 0.6964 | 1.7834 |

**Table.3.** Comparative results using real-time XRP trading data (80% level); training data in curly brackets.

| Trial number | NeuroAMI $_{MAPE\{80\%\}}$ | NARXnet$_{MAPE\{80\%\}}$ | LSTM$_{MAPE\{80\%\}}$ |
|---|---|---|---|
| 1 | 0.4569 | 0.9091 | 1.9076 |
| 2 | 0.4569 | 0.9091 | 2.0030 |
| 3 | 0.4569 | 0.9091 | 2.0293 |
| 4 | 0.4569 | 0.7273 | 1.9787 |
| 5 | 0.4569 | 0.4545 | 2.3386 |
| **Mean:** | 0.4569 | 0.7818 | 2.0514 |

The results in Tables 1 to 3 shows that the NeuroAMI MAPE is consistent across all the trials which is also the case for the different percentage training data inputs as it gave similar MAPE estimates; on the other hand, the NARXnet and LSTM techniques exhibited stochasticity in their reported MAPE estimates.

The results also clearly shows that NeuroAMI outperformed the NARXnet and LSTM techniques at the 40%, 60% and 80% levels (see mean values). In particular, it can be seen that on average, the proposed NeuroAMI is about 2 times better than the NARXnet technique.

## 5. Conclusions and Future Work

This research has proposed a web-based AI tool that can support trading in financial markets such as the Cryptocurrency Exchange (CRYPTEX) markets. The new system (NeuroAMI) uses unconventional neural techniques that draw inspiration from intelligent processing in auditory cortex. The proposed NeuroAMI system has been applied to real-time data obtained from a CRYPTEX market.

The predictive real-time functionality of the proposed NeuroAMI system was deployed and tested on the LUNO financial exchange which represents a CRYPTEX market.

The results of simulation experiments based on the Mean Absolute Percentage Error (MAPE) evaluation metric and using the NeuroAMI technique with real-time data are compared with two existing neural models - the NARXnet and progressive LSTM. The results showed that the proposed new system is better than the existing ones with respect to progressive MAPE performance, and consistency in results.

Hence, the NeuroAMI technique is highly recommended as an alternative and more bio-inspired artificial neural strategy for CRYPTEX markets.

In future, attempts at enhancing the NeuroAMI system to improve MAPE performance will be investigated by employing dynamic optimization strategies. Also, detailed studies on the NeuroAMI operating parameters will be equally investigated.

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## References

Anghel, D. G. (2020). A reality check on trading rule performance in the cryptocurrency market:Machine learning vs. technical analysis. *Finance Research Letters*, 101655.

Cui, Y., Ahmad, S., & Hawkins, J. (2016). Continuous online sequence learning with an unsupervised neural network model. *Neural computation*, *28*(11), 2474-2504.

Dutta, A., Kumar, S., &Basu, M. (2020). A Gated Recurrent Unit Approach to Bitcoin Price Prediction. *Journal of Risk and Financial Management*, *13*(2), 23.

Fayek, H. M. (2017). MatDL: A lightweight deep learning library in MATLAB. *Journal of Open Source Software*, *2*(19), 413.

Houssein, E. H., Dirar, M., Hussain, K., & Mohamed, W. M. (2020). Assess deep learning models for Egyptian exchange prediction using nonlinear artificial neural networks. *Neural Computing and Applications*, 1-23.

Miura, R., Pichl, L., &Kaizoji, T. (2019, July). Artificial Neural Networks for Realized Volatility Prediction in Cryptocurrency Time Series. In *International Symposium on Neural Networks* (pp. 165-172). Springer, Cham.

Osegi, E. N., & Anireh, V. (2020). AMI: an auditory machine intelligence algorithm for predicting sensory-like data. *Computer Science*, *5*(2), 71-89.

Osegi, E. N. (2021). Design and Implementation of a Web-Based AI Tool for Real Time Trading In Financial Markets. Diploma Thesis. National Open University of Nigeria (NOUN).

Osegi, E. N. (2023). Neuronal Auditory Machine Intelligence (Neuro-AMI) In Perspective. http://dx.doi.org/10.13140/RG.2.2.10131.45605.

Omane-Adjepong, M., Alagidede, P., & Akosah, N. K. (2019). Wavelet time-scale persistence analysis of cryptocurrency market returns and volatility. *Physica A: Statistical Mechanics and its Applications*, *514*, 105-120.

Shintate, T., & Pichl, L. (2019). Trend prediction classification for high frequency bitcoin time series with deep learning. *Journal of risk and Financial management*, *12*(1), 17.