Predicting Ethereum Fraudulency using ChaosNet

Anurag Dutta
Liton Chandra Voumik2 (litonvoumik@gmail.com)
https://orcid.org/0000-0002-9612-7350
Samrat Ray

Research Article

Keywords: Crypto – Currency, Blockchain, ChaosNet, GLS Neurons, Artificial Neural Network

Posted Date: January 30th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2513355/v1

License: © This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License
Abstract

Cryptocurrencies are in high demand right now, perhaps because of their volatile nature and untraceable difficulties. Bitcoin, Ethereum, Dogecoin, and others are just a few. This research seeks to identify falsehoods and probable fraudulences in Ethereum transactional processes. We have provided this capability to ChaosNet, an Artificial Neural Network constructed using Generalized Luroth Series maps. At many spatiotemporal scales, Chaos has been objectively discovered in the brain. Several synthetic neuronal simulations, including the Hindmarsh-Rose model, possess Chaos, and individual brain neurons are known to display chaotic bursting phenomenon. Although Chaos is included in several Artificial Neural Networks (ANNs), for instance, the Recursively Generating Neural Networks, no ANN exist for classical tasks that is fully made up of Chaoticity. ChaosNet uses the chaotic GLS neurons' topological transitivity property to perform classification problems with cutting-edge performance the pool of data including lower training sample count. This synthetic neural network can perform categorization tasks by gathering from a definite amount of training data. ChaosNet utilizes some of the best traits of network subjected to biological neurons, which derive from the strong Chaotic activity of individual neurons, to solve difficult classification tasks on par with or better than standard Artificial Neural Networks. It has been shown to require much fewer training samples.

1. Introduction

Learning through techniques as Machine Learning (ML) and Deep Learning is now possible. Thanks to the development of Artificial Intelligence. [1] They have gained appeal and are some hot topics, with applications in practically every sector of human endeavours. Among these are, to name a few, Voice Processing [2], Computer Vision [3], Cyber Security [4], and Medical Diagnosis [5]. Despite being influenced by the biological brain, the learning and memory encoding processes in humans are not directly tied to these algorithms. These artificial neural networks’ (ANNs) [6] learning processes for changing masses and biases are standardized on optimization strategies and the minimizing of loss and error functions. As larger pool of nascent data is fed into the system, the ANNs currently use a huge count subjecting hyperparameters [7] that are fixed via some ad hoc approach for better prediction. These synaptic alterations are based primarily on facts and lack or have little solid theoretical support. Additionally, these methods need a huge quantity of training data to be able to accurately forecast or classify the distribution of the target classes.

ANNs have achieved great success, but when it comes to doing tasks like natural language processing [8], they fall well short of the human intellect. Researchers are concentrating on creating biologically inspired algorithms and architectures in order to utilize the remarkable learning capabilities of the Homo sapiens’ brain alongside better understandability of the same. This is being done in relation to memory encoding and learning. One of the brain's most intriguing traits is its capacity for "Chaos" – the phenomenon whereby straightforward deterministic nonlinear systems exhibit complex unexpected and random – like behavior. Electroencephalogram (EEG) signals [9] are known to have chaotic dynamics [10]. A neural system's sensitivity to little changes in internal functioning characteristics aids in producing
the optimal response to various influences. This characteristic resembles the chaotic systems' dynamical characteristics. Furthermore, it is evident that the brain is constantly switching between several states rather than returning to homeostasis after a transient. For this reason, it is hypothesized that the brain can display a variety of behaviors, including periodicity in orbits, weak nature of chaotic dynamics, as well as strong nature of chaos, depending on the functional parameters of the neurons. Cerebral networks, that are made up of trillions of neurons, exhibit chaotic activity, but so is the scenario for the dynamics of individual neurons at both the cellular as well as subcellular levels. These neurons’ ability to build impulse trains is what allows the brain to transmit and store information. When various ions pass across the axonal membrane and affect the voltage across it, action potentials or impulses are produced. For the communication bridging the ion passages and the axonal membrane, Huxley and Hodgkin initially put forth a dynamic system's model that is able to produce accurate action potentials [11]. Later, it was suggested to use its streamlined counterparts, for instance, the Hindmarsh-Rose [12] and the Fitzhugh-Nagumo model [13][14]. These models all display chaotic behavior.

Recurrent neural networks [15][16] are one type of artificial neural network that exhibits chaotic dynamics; however, as far as we are aware, none of these proposed architectures thus far subjecting classification tasks show chaos at the details of individuality of neurons. Though, other chaotic neuron models have been proposed as a theoretical description for memory encoding inside our brain.

One of these models is the Aihara model [17], that has been applied to cognitive tasks in the network’s erratic periodic orbits [18]. Freeman, Kuzma, and colleague developed chaotic simulations that were motivated by the mammalian sensory pathway to demonstrate the process of memorizing scents [19–21]. Chaos in neural networks has also been studied by Tsuda and others. Globally coupled chaotic maps' dynamical properties have been studied by Kaneko, who hypothesized that these networks would be able to handle biological data.

Generalized Luröth Series (GLS) 1D chaotic map neurons make up ChaosNet, an artificial neural network (ANN) [22]. This network can learn from a small number of training examples to perform classification tasks. To utilize some of the best characteristics of biological neural networks, ChaosNet was developed. It has been demonstrated that, while using significantly fewer training samples than traditional ANNs, it can perform difficult classification tasks on par with or better than conventional ANNs.

ChaosNet, which was inspired by biological neurons, uses a property similar to the "spike-count rate" of the firing of chaotic neurons as a neural code for learning. Additionally, the network can exhibit a hierarchical architecture that can incorporate information as it is transmitted to deeper, higher levels of the network. Generalized Luröth Series, or GLS, is a piecewise linear 1D chaotic map that represents the neuron that we suggest. Examples of GLS include the well-known Tent map, Binary map, and its skewed relatives. The sorts of GLS neurons that are employed in ChaosNet are

\[ T_{Skew-Binary}(x) = \begin{cases} 
\frac{x}{b} & 0 \leq x < b \\
\frac{(x-b)}{(1-b)} & b \leq x < 1 
\end{cases} \]
and

\[ T_{Skew-Tent}(x) = \begin{cases} \frac{x}{b} & 0 \leq x < b \\ \frac{(1-b)(1-x)}{(1-b)} & b \leq x < 1 \end{cases} \]

Figure 2. The architecture of ChaosNet [24] Luroth neural networks for purposes relating to classification. \( C_1, C_2, \ldots, C_n \) are the unit dimensional GLS neurons. Each neuron initially exhibits \( q \) units of normalized neuronal activity. The input to the network, or the normalized collection of stimuli, is denoted by the \( \{x_i\}_{i=1}^n \). When a GLS neuron \( C_i \)'s chaotic activity value \( A_i(t) \), starting from initial neural activity \( (q) \), reaches the \( \epsilon \)-neighborhood of stimulus, it stops firing chaotically. This neuron has a “firing time” of \( N_i \) ms. \( A_i(t) \) contains topological transitivity symbolic sequence feature \( p_i \). This feature is extracted from \( A_i(t) \) of the \( C_i \)'s GLS-neuron.

A cryptocurrency [25], often called as a crypto-currency or just a "crypto," is a sort of digital money that is supported or maintained by no single central body, such as a bank or government. It is a decentralized means of verifying that the parties to a transaction genuinely have the funds they claim to have, eliminating the need for traditional middlemen like banks when money is being transferred between two businesses. Digital ledgers, which are computerized databases that use safe encryption to protect transaction records, regulate the production of new currencies, and confirm ownership transfers, are used to keep individual coin ownership records. Cryptocurrency is typically not authorized by a centralized unit and isn't exist in tangible form like paper money. In contrast to digital currencies managed by a central bank, cryptocurrency usually employs decentralized control (CBDC). When a cryptocurrency [26] is coined, generated in anticipation of issuance, or released by a single issuer, it is considered centralized. When utilized with decentralized governance, each cryptocurrency uses distributed ledger technology, generally a blockchain, which acts as a public database of financial transactions. Currency, commodities, and stocks are traditional asset classes and macroeconomic indicators with moderate sensitivity to cryptocurrency returns.

Financial or personal gain is the intended outcome of cryptocurrency fraud, which is a dishonest behavior in the cryptocurrency business. By convincing their unwitting victims to take an action, such as clicking on a link or disclosing personal information, scammers, and hackers on the internet hope to make some quick cash.

For cryptocurrency scams, criminals frequently try to gain access to a victim's digital wallet in order to steal their cryptocurrency assets. Typically, they will ask you to connect your wallet to a bogus website or deceive you into giving them access to your wallet's private keys. Cryptocurrency Fraudulences can be of many types, like,

Phishing: Even though fraudsters are nothing new, individuals continue to fall for them every day. A malicious hyperlink in an inbox or a bogus website that occasionally uncannily resembles its genuine
counterpart can both be used in phishing scams. Your personal information, such as your internet passwords or the private keys to your crypto wallet, may be stolen using the link or website.

Middle Man attacks: Man-in-the-middle assaults are a technique used by con artists to obtain your personal information, much to phishing scams. To access your bitcoin wallet or private account information, a guy will disrupt a Wi-Fi session on a broad network as opposed to doing so through links. Use a VPN to secure your data while depositing cryptocurrency to avoid this.

Investors’ Scam: Investment managers that offer to help you make significant improvements on your portfolio may be posing as fraudsters. These dishonest people will entice customers to transmit them cryptocurrencies and may even promise to increase its worth by 50 times. Forbes Advisor does caution, though, that "if you comply with their demands, kiss goodbye to your cryptocurrency." With this scam, the con artist is probably deceiving several people, taking their cryptocurrency with them, and then vanishing.

Pump & Dump: This is true for both regular stock markets and cryptocurrency marketplaces. When a coin launches, its owners sell all their holdings, which is known as a pump and dump strategy. As a result, the price reaches an erroneous peak before dropping sharply after the initial public offering is over. False statements made about a project that cause a lot of hype can make these tactics worse.

2. Ethereum

Ethereum [27] is, at its core, a proof-of-stake decentralized global software platform. It is well known for its ether cryptocurrency (ETH). Anyone can use Ethereum to develop any safe digitizing. It has a currency designed to recompense users for work done in support of the blockchain, but if accepted, users may also use it to exchange for physical goods and services. Ethereum has the characteristics of being extensible, adaptable, anonymous, and decentralized. It is the decentralized cryptocurrency of choice for programmers and businesses building technology on top of it to alter multiple industries as well as how people go about their daily lives. In late 2013, Vitalik Buterin, a developer & cofounder at Bitcoin Magazine, introduced Ethereum [28] as a mechanism for building decentralized apps in a white paper. Buterin told the Bitcoin Kernel technicians that the nature of blockchain technology may derive from applications apart from currency and suggested that a better sophisticated language for designing apps was needed. In early 2014, Ethereum Switzerland GmbH, a Swiss corporation, began official the development of the software underpinning EthSuisse [29]. The concept of holding executable smart contracts on the blockchain had to be outlined prior to it being implemented in software. This work was done in the Ethereum Virtual Machine specification by Gavin Wood, the Ethereum Yellow Paper's then-chief technical officer. Following that, the Stiftung Ethereum [30] (Ethereum Foundation) was established as a Swiss non-profit organization. From July through August 2014, an online public crowd sale was held in which people bought the Ethereum value token (ether) with bitcoin, another digital money. Although Ethereum's technical advances were first lauded, concerns regarding its scalability and security were raised. To construct and achieve consensus on an ever-expanding collection of “blocks,” or groups of transactions known as a blockchain, Ethereum is an epicondyle [31], or virtual collective [32], of computer
nodes. For the sequence that must come before each block in order for it to be considered authentic, each block has a distinct identifier. When a base station adds a block to its chain, it executes the actions in the block in the designated order, each of which has the potential to alter the ETH balance [33] and other rack values of Ethereum accounts. In a Merkle tree, the "state," or collection of these totals and values, is held on the node apart from the blockchain. Only a limited portion of the network, known as its "peers," are accessible to each node. Every time a node wants to add a new transaction [34] [35] to the chain, it sends copies of the transaction to all of its contemporaries, who then send copies to all of their contemporaries, and so forth. It spreads throughout the network in this way. All these fresh transactions are kept track of by a group of nodes known as miners, who use them to build new blocks and distribute them to the remainder [36] of the network. Every time a node receives a block, it verifies the validity of the block and of each transaction contained inside. If the block is found to be valid, it is added to the blockchain and each transaction is carried out. A node may receive numerous blocks that are vying to succeed a specific block since block generation [37] and broadcasting are permissionless. The node records each valid chain that results from this and routinely discards the shortest one: The Ethereum protocol [38] states that the longest chain is to be taken into consideration at any given time.

3. Dataset Description

We have collected a set of Ethereum Transaction Details using Etherscan API, and ehterscamdb API. The Dataset, has 14 Features namely,

Avgminbetweensenttnx: Minutes between each transaction on average for the account.

Avgminbetweenreceivedtnx: Minutes between transactions received on average for the account.

TimeDiffbetweenfirststand_last(Mins): Between the first and last transaction, in terms of time.

Sent_tnx: Total volume of typical transactions sent.

Received_tnx: Total volume of typical transactions received.

NumberofCreated_Contracts: Total number of contract transactions created

UniqueReceivedFrom_Addresses: Total unique addresses from which transactions were sent to the account

UniqueSentTo_Addresses: Total unique addresses from which transactions were sent from the account

MinValueReceived: Lowest amount of Ether ever received

MaxValueReceived: Highest amount ever paid in Ether

AvgValueReceived: Ever received an average amount in Ether
MinValSent: The smallest amount of ether ever sent

MaxValSent: Highest amount of ether ever transferred

AvgValSent: Average amount of ether transmitted over time

The dataset has been made available online at https://github.com/Anurag-Dutta/Ethereum/blob/19b35453da25b40bb22556c1070cfc79fbb52b2f/Eth_Pub_19122022.csv

4. Chaosfeatureextractor + ml Classifiers

Using ChaosNet Standalone, the performance is okay, but we can do better if we make use of any better ML Classifier as a conjunction to the Chaos Feature Extractor. [39]

ChaosNet uses 3 hyperparameters

INA - Initial Neural Activity

EPSILON_1 - Noise Intensity

DT - Discrimination Threshold

The memory of this Single Internal Neuron is corresponding to the Initial Neural Activity. As individual Machine Learning Classifiers, we have used AdaBoost, and kNN (k Nearest Neighbors). Also, we have made use of ChaosNet Standalone.

The respective values of the hyperparameters for the same was tuned to

INITIAL_NEURAL_ACTIVITY = [0.38]

DISCRIMINATION_THRESHOLD = [0.06]

EPSILON = [0.29]

for Standalone ChaosNet.

INITIAL_NEURAL_ACTIVITY = [0.36]

DISCRIMINATION_THRESHOLD = [0.06]

EPSILON = [0.29]

for ChaosNet Feature Extractor conjugated with AdaBoost.

In 1995, Yoav Freund and Robert Schapire created AdaBoost, a statistical classification meta-algorithm. For their efforts, they received the 2003 Gödel Prize. Combining it with a variety of other learning
approaches can improve its performance. The findings of the other learning algorithms, or "weak learners," are combined to produce a weighted sum that represents the final outcomes of the boosted classifier. Although AdaBoost can be applied to a wide range of classes or limited intervals on the real line, it is most employed for binary classification. AdaBoost is adaptive in the sense that it modifies succeeding weak learners in favor of examples that were incorrectly identified by earlier classifiers. In some cases, it may be less prone to overfitting than other learning methods. It can be shown that the final model converges to a strong learner even if each individual learner's performance is just marginally better than random guessing.

\[
\text{INITIAL\_NEURAL\_ACTIVITY} = [0.039]
\]

\[
\text{DISCRIMINATION\_THRESHOLD} = [0.070]
\]

\[
\text{EPSILON} = [0.023]
\]

for ChaosNet Feature Extractor conjugated with k Nearest Neighbors.

One of the simplest supervised learning-based nonparametric machine learning algorithms is K-Nearest Neighbor. Assuming that new cases and data are similar to existing cases, classifying new cases into categories that are most similar to existing categories, storing all relevant data, and based on similarity putting fresh data into categories. Therefore, it is simple to categorize new data into the relevant categories using the K-NN method. Although K-NN algorithms can be applied to classification and regression problems, they are most frequently utilized for classification issues. In other words, no presumptions regarding the underlying data are made. It is also known as a delayed learning algorithm since it saves the dataset and modifies it during classification rather than instantly learning from the training set. The k-NN algorithm only keeps the training phase dataset, and it classifies fresh data into categories that are like the new data as it comes in.

In order to evaluate performance, we used the macro F1-score. The F1 score can be conceived of as a harmonic mean of precision and recall, where 1 being the highest and 0 being the worst. Precision and recall are both equally important in determining the F1 score; "macro" computes the measurements for each label and derives their unweighted mean. Label imbalance is not considered in this. The confusion matrix is used to calculate this measure. Mathematically,

\[
\text{MacroF1Score} = \frac{F1Score_{Class_1} + F1Score_{Class_2} + \ldots + F1Score_{Class_n}}{n}
\]

\[
\text{MacroF1Score} = \frac{1}{n} \left( \sum_{i=1}^{n} F1Score_{Class_i} \right)
\]

where,
5. Conclusion

In the field of machine learning, making decisions when unusual events are present is a difficult task. This is because unusual occurrences have few data examples, and the issue is ultimately one of imbalanced learning. In this work, we have taken use of Neurochaos Learning (NL) architectures' usage of ChaosFEX (CFX) feature modification for imbalanced learning. Since, Cryptocurrencies are in its very nascent stage currently, and due to their masking nature, finding data involving transaction in the Ethereum is quite difficult, and not much can be obtained from that. Like, even if we manage to snoop into the transaction details, the details won't be necessarily sufficient to fulfil the requirements of the classical ML Classifier Algorithms. In this work, we have tried to make use of ChaosNet along with its indigenous Feature Extractor to try out the prediction of possible fraud in the Ethereum Transaction. We made use of the Standalone ChaosNet, that gave us a F1 Score of 0.58 for Training, and 0.57 for Testing, which isn't a good hold. Further, we have made use of the ChaosNet Feature Extractor assisted with Adaptive Boosting to get a F1 Score of 0.81 for Training, and 0.66 for Testing. Finally, we made use of the ChaosNet Feature Extractor assisted with k – Nearest Neighbors to get a F1 Score of 0.79 for Training, and 0.78 for Testing, which is the maximum we can get of it. So, we can conclude of by saying that the ChaosNet Feature Extractor assisted with k – Nearest Neighbors is the best for Predicting Possible Fraudulences in the Ethereum Transaction Dataset. Notably, the F1 Scores used here, are the Macro F1 Score.

\[
F1_{\text{Score}}_{\text{Classi}} = \left( \frac{2 \times \text{Precision}_{\text{Classi}} \times \text{Recall}_{\text{Classi}}}{\text{Precision}_{\text{Classi}} + \text{Recall}_{\text{Classi}}} \right)
\]

\[
\text{Precision}_{\text{Classi}} = \left( \frac{\text{TruePositive}_{\text{Classi}}}{\text{TruePositive}_{\text{Classi}} + \text{FalsePositive}_{\text{Classi}}} \right)
\]

\[
\text{Recall}_{\text{Classi}} = \left( \frac{\text{TruePositive}_{\text{Classi}}}{\text{TruePositive}_{\text{Classi}} + \text{FalseNegative}_{\text{Classi}}} \right)
\]
Data, code, and supporting materials are publicly available via https://github.com/Anurag-Dutta/Ethereum publicly available.

Future Scopes of Research includes the Chaos Feature Extractor being adjunct with several other ML Algorithms that would give a Major F1 Score greater than 0.78.

References


Figures
Figure 1

Neurochaos Learning [23]
The architecture of ChaosNet [24] Luroth neural networks for purposes relating to classification. $C_1, C_2, \ldots, C_n$ are the unit dimensional GLS neurons. Each neuron initially exhibits $q$ units of normalized neuronal activity. The input to the network, or the normalized collection of stimuli, is denoted by the $\{x_i\}_{n=1}^n$. When a GLS neuron $C_i$'s chaotic activity value $A_i(t)$, starting from initial neural activity ($q$), reaches the $\varepsilon$-neighborhood of stimulus, it stops firing chaotically. This neuron has a “firing time” of $N_i$ ms. $A_i(t)$ contains topological transitivity symbolic sequence feature $p_i$. This feature is extracted from $A_i(t)$ of the $C_i$'s GLS-neuron.

**Figure 2**

```
\[ x_1 \rightarrow G_1 \rightarrow q \rightarrow N_1 \rightarrow \text{ChaosNet} \rightarrow \text{Output} \]
\[ x_2 \rightarrow G_2 \rightarrow q \rightarrow N_2 \rightarrow \text{Machine Learning} \rightarrow \text{Output} \]
\[ x_n \rightarrow G_n \rightarrow q \rightarrow N_n \rightarrow \text{Feature Transformation} \rightarrow \text{Classification} \]
```

**Figure 3**

Figure 2. Architecture proposing Conjunction of the Chaos Feature Extractor with standard ML Classifiers. The three actions involved includes Feature transformation, feature extraction from Neurochaos, and classification are the first two steps. ChaosNet or any other ML classifier could be selected as the chosen classifier.