# Causality Preserving Chaotic Transformations and Classification using Neurochaos Learning

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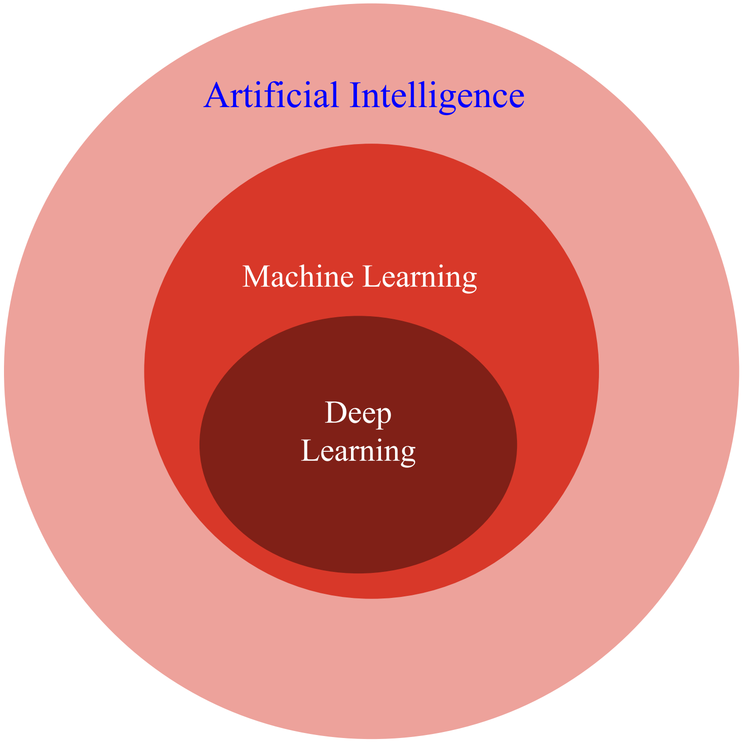
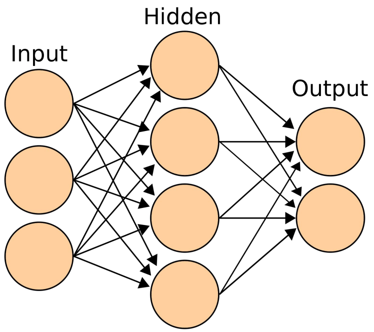
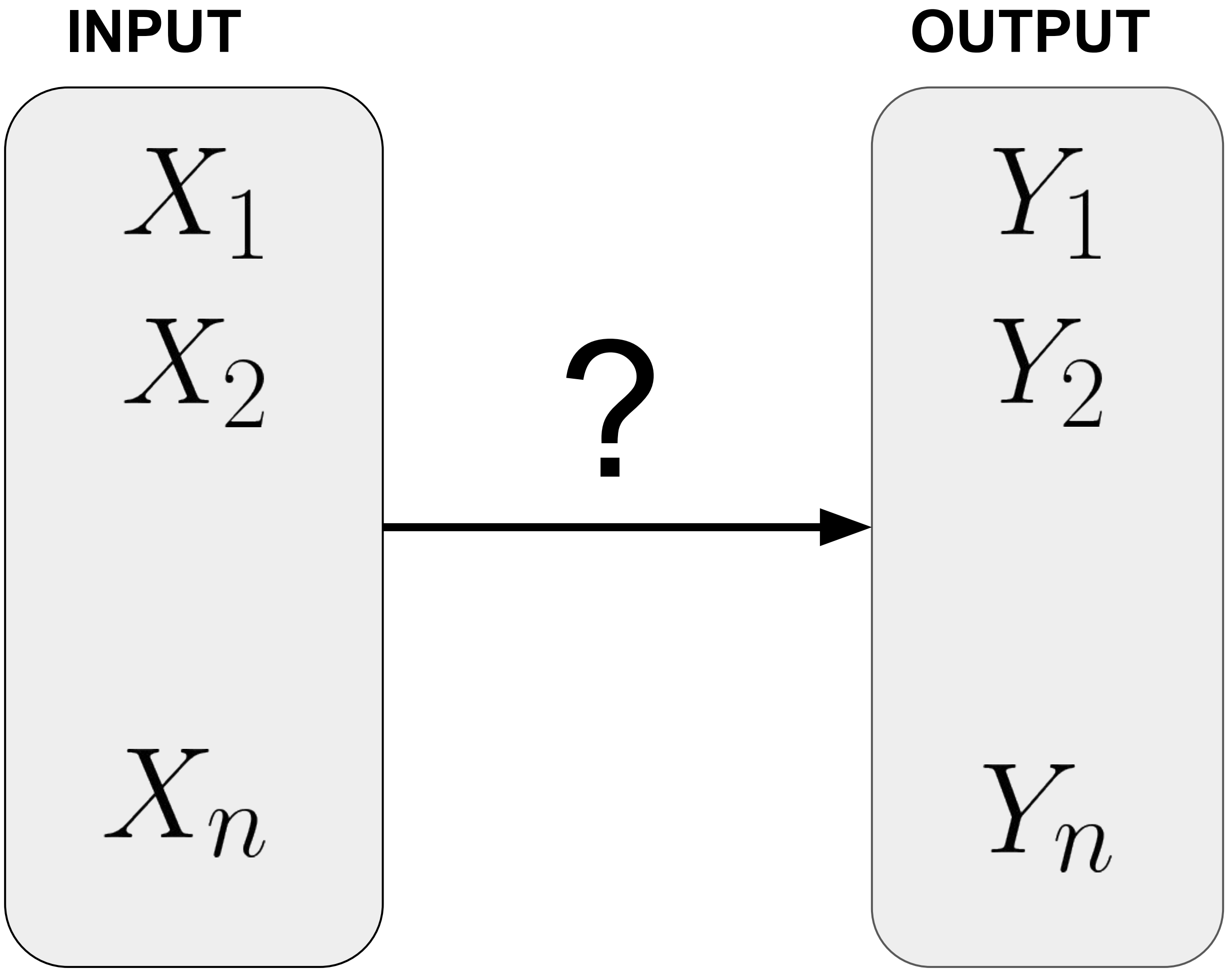
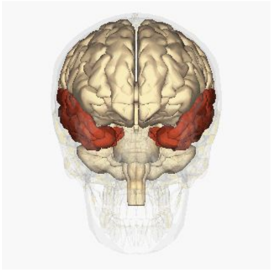
# Introduction




Issues with **trustworthiness** and **interpretability**.



Human decision making relies on **reasoning** and **causal inference**.

In this work, we focus on **causality detection** from **time-series data** (without assumption of any causal model) and use a recently proposed **brain inspired learning algorithm** namely **Neurochaos Learning (NL)** [1,2].

[1] N.B. H, Nagaraj N. When Noise meets Chaos: Stochastic Resonance in Neurochaos Learning. *Neural Networks*. 2021;143:425-435. doi:10.1016/j.neunet.2021.06.025
[2] Balakrishnan H, Kathpalia A, Saha S, Nagaraj N. ChaosNet: A chaos based artificial neural network architecture for classification. *Chaos: An Interdisciplinary Journal of Nonlinear Science*. 2019;29(11):113125. doi:10.1063/1.5120831

# Objectives of the Study

- O1: The efficacy of **Neurochaos Learning (NL)** in cause-effect classification and compare the same with Deep Neural Network (DNN), 1D Convolutional Neural Network (1D CNN), and Long Short Term Memory (LSTM).
- O2: Does success in cause-effect classification imply **preservation of causality**?
- O3: Can **NL** use a **transfer learning framework** for **cause-effect classification?**

# Datasets

- Coupled Autoregressive (AR) processes
- Coupled 1D Chaotic maps in Master-Slave configuration
- Predator (*Didinium Nasutum*) and Prey (*Paramecium Aurelia*) real world data [3].

Table 1: Train-Test distribution for the simulated datasets.

| Class | Traindata | Testdata |
|---|---|---|
| Class-0 | 801 | 199 |
| Class-1 | 799 | 201 |
| Total | 1600 | 400 |

Each of the data instances are of length 2000, after removing the initial 500 samples (transients) from the time series.

[3]. Brendan G Veilleux. The analysis of a predatory interaction between didinium and paramecium. *Master's thesis. University of Alberta, Edmondton, 1976.*

# Experiments and Discussions

# Coupled AR Processes

$$M(t) = a_1 M(t-1) + \gamma r(t),$$
$$S(t) = a_2 S(t-1) + \eta M(t-1) + \gamma r(t),$$

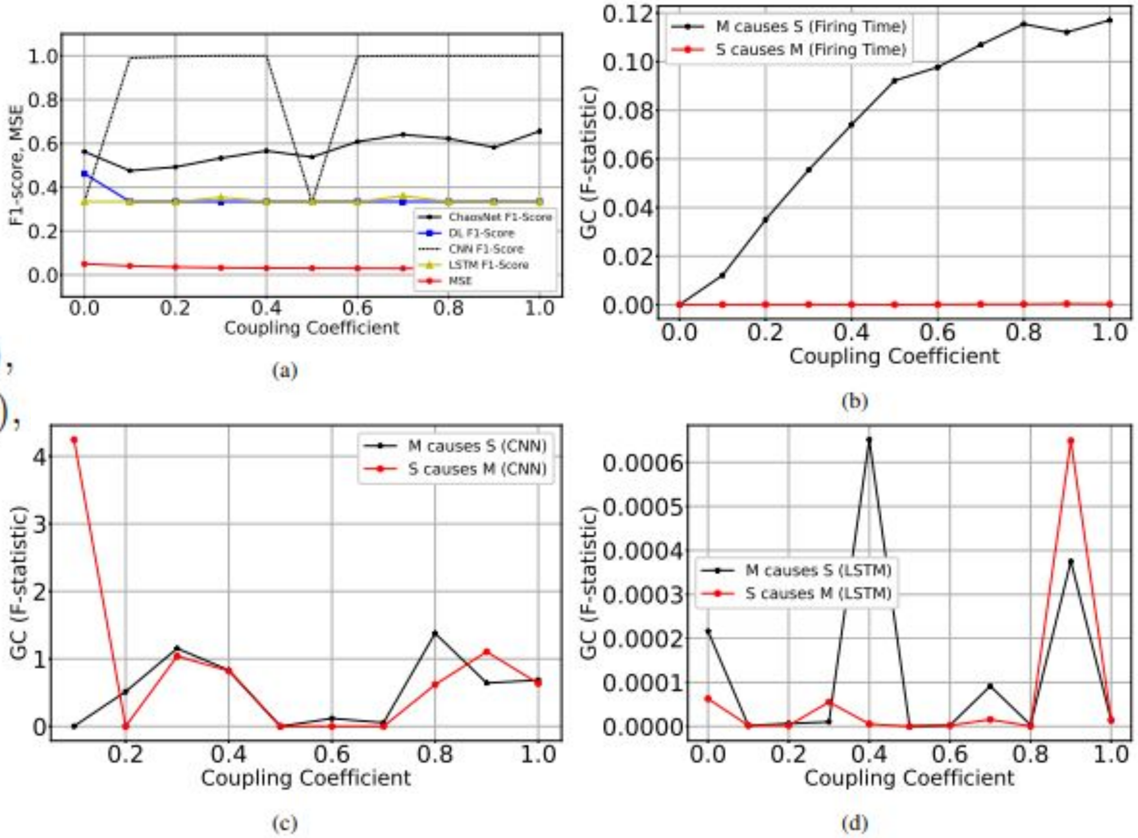



Figure S1: (a) Performance comparison of ChaosNet with five layer DNN, 1D CNN, and LSTM for the classification of cause-effect for timeseries data generated from coupled AR processes. (b) GC vs Coupling Coefficient for the firing time feature (ChaosFEX feature) extracted from the input layer of NL. (c) GC vs Coupling Coefficient for features extracted from the second last layer of 1D CNN architecture. (d) GC vs Coupling Coefficient for features extracted from the second last layer of LSTM architecture.

# Coupled AR Processes

$$M(t) = a_1 M(t-1) + \gamma r(t),$$
$$S(t) = a_2 S(t-1) + \eta M(t-1) + \gamma r(t),$$

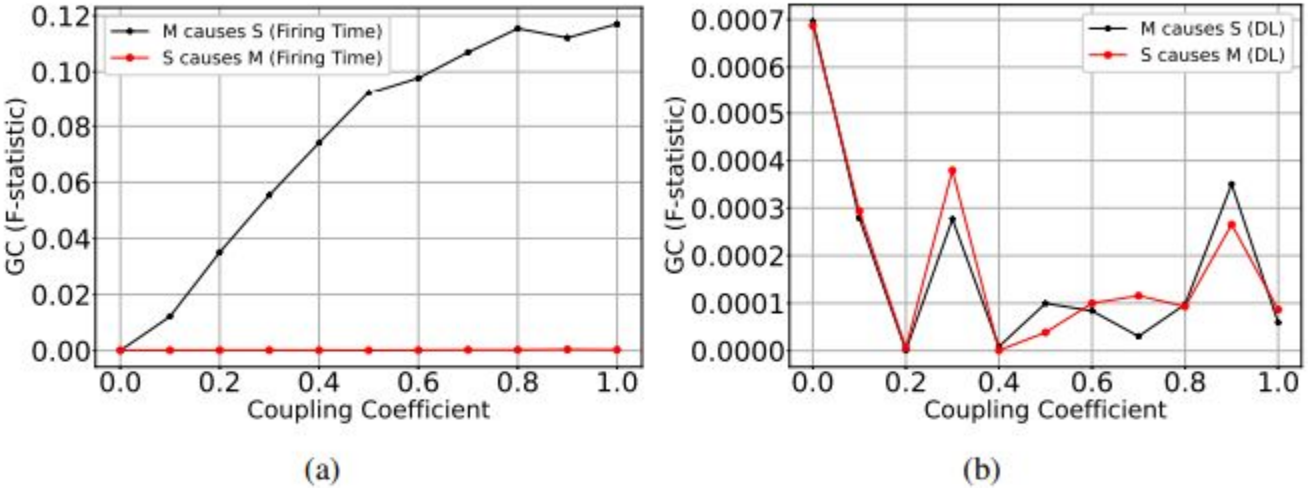



Figure 1: (a) GC vs. coupling coefficient for the firing time feature extracted from the coupled AR processes. The ChaosFEX settings are $q = 0.78$, $b = 0.499$, and $\epsilon = 0.171$. The GC F-statistic is computed from 50 trials. (b) GC vs. coupling coefficient for DL features extracted from the fourth hidden layer of a five layer neural network. The GC F-statistic is computed from 50 trials.

# Coupled Chaotic Map in Master- Slave Configuration

$$M(t) = T_1(M(t-1)),$$
$$S(t) = (1-\eta)T_2(S(t-1)) + \eta M(t-1),$$

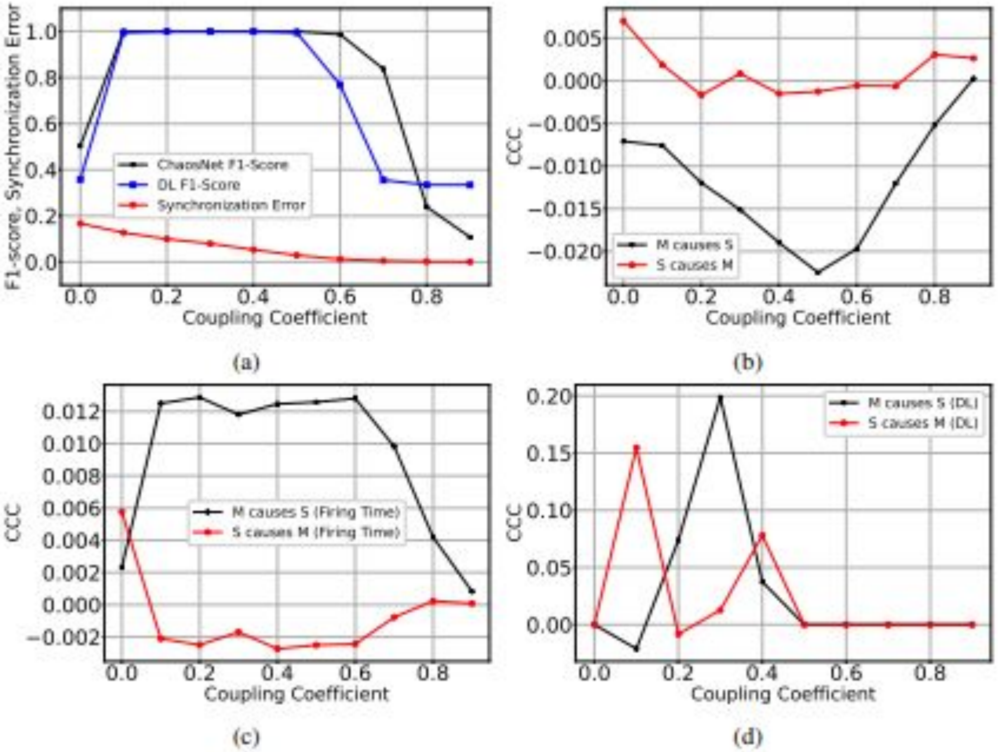



Figure 2: (a) Performance comparison of ChaosNet and five layer DNN for the classification of cause-effect for 1D coupled skew tent map in master-slave configuration. (b) CCC vs Coupling Coefficient for the raw data corresponding to 1D chaotic skew tent map in master-slave configuration. (c) CCC vs Coupling Coefficient for firing time (ChaosFEX feature) corresponding to 1D chaotic coupled skew tent maps in master-slave configuration. (d) CCC vs Coupling Coefficient for features extracted from the second last layer of five layer deep neural network corresponding to 1D chaotic coupled skew tent maps in master-slave configuration.

# Predator - Prey Dataset

Table 2: Cause-effect preservation of the prey-predator real world data using CCC.

| Class | CCC (rawdata) | CCC (NL, firing time) | DL |
|---|---|---|---|
| Predator $\rightarrow$ Prey | 0.1160 | 0.0484 | Unable to compute |
| Prey $\rightarrow$ Predator | -0.0210 | 0.0050 | Unable to compute |

**NL preserves causality whereas DL fails.**

# Conclusions

- Neurochaos Learning (ChaosNet) outperforms a five layer deep learning architecture and LSTM in the case of both chaotic tent maps and AR processes.
- In the case of AR processes, 1D CNN performs better than ChaosNet for several values of coupling. Whereas, in the case of coupled chaotic skew-tent map, ChaosNet outperforms all the other methods including 1D CNN.
- Features extracted from DNN, 1D CNN and LSTM failed to preserve the cause-effect relationship as measured by GC and CCC for coupled AR processes and skew tent map master slave system.
- Features extracted from the input layer of ***NL preserves the cause-effect relationship as measured by GC and CCC***.

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