Computational Models of Neuronal Constellation

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***Abstract* - This research examines the decoding of behavioural categories from neural spike trains through computational models and machine learning methods. The necessary datasets were supplied, including the output of a small network of six distinct real neurons recorded while an animal, confined in a maze, moves to a designated location upon hearing a sound to obtain a reward. The approach used in this research entailed the generation of artificial spike trains through interconnected Leaky Integrate-and-Fire (LIF) models, the estimation of firing rates, and the use of several classifiers to decode behavioural categories. A 200 ms time frame was identified for firing rate estimation that yielded best decoding performance. The Decision Tree classifier attained the maximum accuracy, recording 74.1% for the EME dataset and 77.2% for the ORA dataset, in interpreting behavioural categories from actual firing rates. Artificial spike trains, although inferior to actual data in performance, facilitated above-chance decoding (62.7% for EME, 47.6% for ORA), indicating that the models encapsulated substantial behaviourally pertinent characteristics of brain activity.**

KEYWORDS:
Neurons, Computational Models, Decode, Datasets, Spikes and Firing Rates, machine learning, Leaky Integrate-and-Fire, Python.

THE PURPOSE:

The aim of this project is to develop a computational model for the above concrete black-box system in comparison to the six neurons to aid decode the results of the four behavioral categories of the datasets provided.

I. METHODOLOGY

The project was implemented utilising Python, which offered a comprehensive ecosystem of libraries and tools for data processing, analysis, and machine learning. Essential libraries utilised included NumPy, pandas, and scikit-learn for computation and modelling. The full python code is provided in Appendix G.

Spiking Models

This neural analysis project will primarily use Leaky Integrate-and-Fire (LIF) model, a simplistic yet robust representation of neuronal dynamics.

Leaky Integrate-and-Fire Model

The LIF model is a simplification of the more intricate Hodgkin-Huxley model, preserving essential characteristics of neural behaviour. The objective is to capture the fundamental patterns of neural firing while avoiding the computational complexities of precise biophysical models [1].

The fundamental LIF model is defined by the following differential equation:

$$\tau_m \frac{dU}{dt} = -U(t) + R * I(t)$$

Where:

- $U(t)$ is the membrane potential
- τ is the membrane time constant
- R is the membrane resistance
- $I(t)$ is the input current

When $U(t)$ reaches a threshold Uth, a spike is generated, and its membrane potential $U(t)$ will reset to a resting potential [2].

Extended LIF Model

An enhanced version of the LIF model that incorporates an absolute refractory period (ARP), and a background current will be used. This model offers a more accurate depiction of neural behaviour by integrating [3]:

1. **Absolute Refractory Period**: A short duration following an action potential during which the neuron is incapable of firing again.
2. **Background Current**: A constant current that reflects the neuron's baseline activity.

The comprehensive model is defined by:

$$\tau_m \frac{dU}{dt} = -(U(t) - U_{rest}) + R * I(t) + R * I_{bg}$$

Where I_{bg} is the background current.

Firing Rates

Firing rates indicate the mean number of spikes produced by a neuron within a designated time interval. They are essential for interpreting brain information and comprehending the correlation between neuronal activity and behaviour [4].

We define the firing rate as:

$$r(t) = \frac{n \ (spikes\ per\ trials)}{T \ (total\ trial\ duration)}$$

Where $r(t)$ is the firing rate at time t, $\boldsymbol{n}$ is the number of spikes in the time window and T is the duration of the time window.
The firing rates will be calculated using various methods, including:

1. **Spike Count Method**: Counting spikes in fixed time windows [4].
2. **Pearson Correlation analysis**: Analyse p-values in different time windows in 4 trials, ranging from 0 to 1.
    a. This method entails computing p-values for each window across various trials and graphing these p-values on a range of 0 to 1 seconds [5].

This methodology presents numerous benefits:

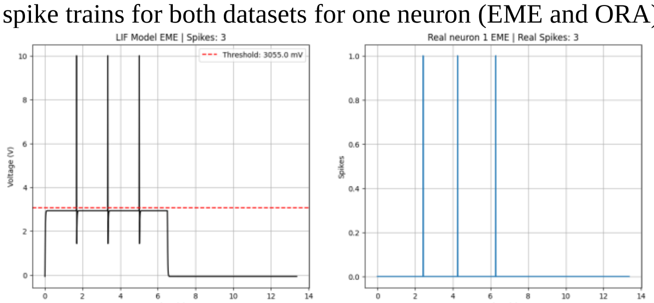
- It offers a statistical quantification of the probability of spike occurrence within each time interval to select the optimal time window (p-value < 0.05).
- It facilitates the comparison of brain activity across various trials.
- It can reveal temporal patterns in brain activation that could remain obscured by smoothing techniques.

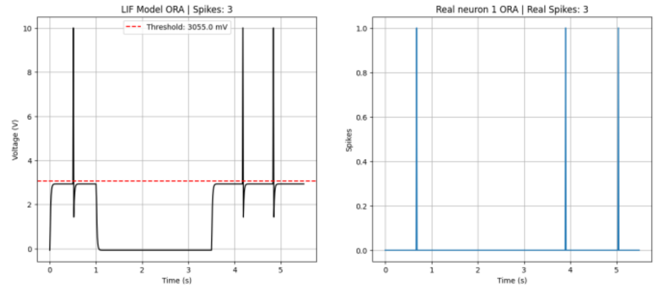
II. First subsection of results

In this section artificial spike trains were generated through the network of interconnected Leaky Integrate-and-Fire (LIF) models. A network of six neurons was established to correspond with the quantity of neurons in the datasets. The objective was to generate artificial spike trains that closely mimic the authentic spike patterns identified in the experimental datasets.

Simulation Results

The network was simulated for 4 aggregated trails which represents 14 seconds for EME and 5 seconds for ORA, using a time step of 0.01 seconds snapshot of the neural network output visible in Appendix A. Figure 1 illustrates the resultant spike trains for both datasets for one neuron (EME and ORA).





(Figure 1- Generated spikes)

Similarity evaluation

To evaluate the similarity between real and artificial spike trains, we used two metrics:

1. Inter-Spike Interval (ISI) comparison
2. Spike count error

ISI Comparison

The distribution of interspike intervals (ISI), indicating the time difference between successive spikes in both real and artificial spike trains, measures the temporal structure of spike generation [6]**.** The ISI is calculated using the formula:

$$ISI = t_{i+1} - t_i$$

Where t_i and t_{i+1} represent the times of successive spikes.
This metric is significant as a neuron's ISI distribution indicates its firing regularity and bursting behaviour. By analysing the ISI distributions of real and artificial spike trains, the fidelity of the artificial model in replicating the temporal firing properties of the actual neuron can be evaluated [6].

Alignment of the ISI distributions between actual and artificial spikes indicates that the artificial model, such as a Leaky Integrate-and-Fire (LIF) model, effectively replicates the temporal dynamics of a real neuron. Nonetheless, if the distributions diverge, it may suggest that the generated spikes are generated at inappropriate times or display distinct firing patterns [6]. The ISI distribution for each neuron on both datasets is found in Appendix B

Spike count error

The Spike Count Error quantifies the difference in the total spike count between real and artificial spike trains, offering an intuitive way to evaluate the accuracy of the Leaky Integrate-and-Fire (LIF) model in generating the correct number of spikes [7]. It is computed with the formula:

$$Spike\ Count\ Error = \frac{N_{real} - N_{artificial}}{N_{real}}$$

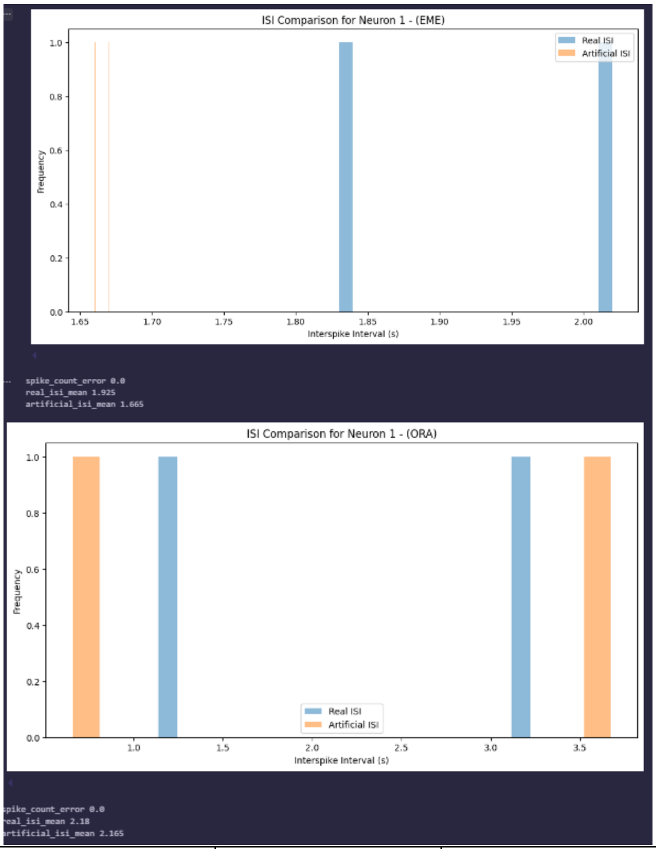
N_{real} and $N_{artificial}$ represent the total counts of spikes in the real and artificial spike trains, respectively.

This metric is essential for verifying that the total activity level, or spike count, of the simulated spike train corresponds with the real data. A low Spike Count Error, generally below 5%, signifies that the artificial model produces spikes at a frequency comparable to that of the real neuron [7].

A low spike count error means that the model accurately reflects the total firing activity, whereas a high error signifies that the model is either over-firing or under-firing compared to the real data.

ISI distributions & Spike count error results

Figure 2 shows the ISI distributions and spike count error for both real and artificial spike trains for neuron 1 on EME & ORA datasets.



Datasets	Real neuron 1 value	Artificial neuron 1 value
EME	**ISI**: 1.925	**ISI**: 1.665 **Spike count**: 0
ORA	**ISI:** 2.18	**ISI:** 2.165 **Spike count**: 0

(Table 2 – ISI & Spike count analyses)

Discussion

The generated artificial spike trains exhibit a considerable resemblance to the actual spike trains in both datasets. The ISI distributions of the artificial data closely resemble those of the actual data, demonstrating relatively low divergence values, and the spike error count is below 5%. This suggests that the implemented LIF network model accurately reflects the temporal properties of actual neurons.

The LIF network model effectively generates artificial spike trains that closely mimic real neural activity in both datasets. Nonetheless, there exists potential for enhancement in obtaining of fine-scale temporal correlations among neurons. For example, a Tsodyks-Markram model, that incorporates mechanisms of short-term synaptic plasticity, including facilitation and depression, could have been implemented. This would enable synaptic strengths to fluctuate dynamically according to recent activity, resulting in more complex and realistic interactions across neurons [8].

III. Second subsection of results

Optimal Firing Rate Estimation

A sliding window strategy was used to optimally determine the firing rates of neurons for both datasets, EME and ORA. The optimal window sizes for calculating firing rates were determined by analysing the Pearson correlation value between the spikes and their respective rates for both real and artificial neurons in 4 distinct trails, as detailed in Appendix C and D.

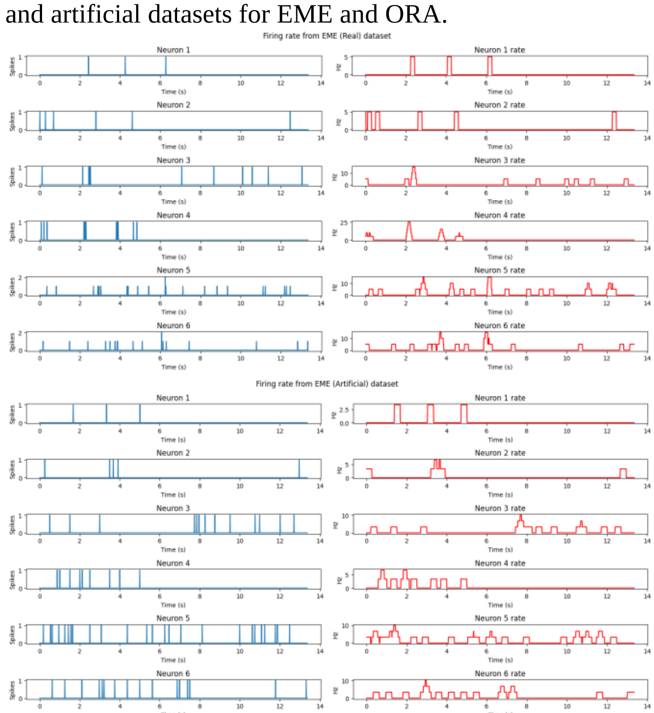
Evaluation and Comparison

The similarity between the real and artificial firing rates was evaluated through:

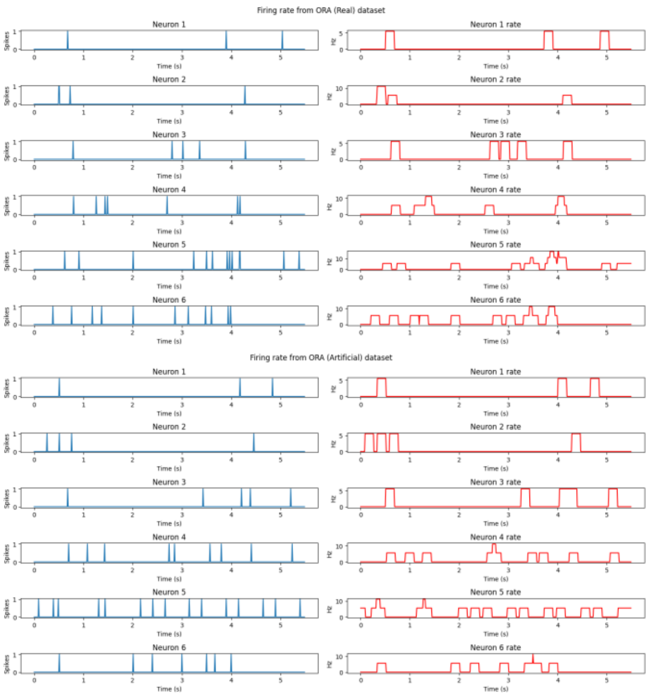
1. Correlation Coefficients: Correlations between real and artificial firing rates were computed for each neuron.
2. Visual Analysis: Overlayed plots of firing rates over time provided a qualitative assessment of similarity.

Results

Figure 3 and 4 illustrates the smoothed firing rate for the real and artificial datasets for EME and ORA.



(Figure 3: Visual Analysis – EME dataset. Real and Artificial)



(Figure 4: Visual Analysis – ORA dataset. Real and Artificial)

Figure 5 and 6 illustrates the firing rate correlation results for the real and artificial datasets for EME and ORA.

Corrolation rate and p-Value from EME (Real) Dataset

	Neuron	Correlation Coefficient	P-Value
0	Neuron 1	0.218777	5.950898e-16
1	Neuron 2	0.233625	4.948102e-18
2	Neuron 3	0.226902	4.515279e-17
3	Neuron 4	0.298801	5.614610e-29
4	Neuron 5	0.229024	2.263698e-17
5	Neuron 6	0.229213	2.128455e-17

Corrolation rate and p-Value from EME (Artificial) Dataset

	Neuron	Correlation Coefficient	P-Value
0	Neuron 1	0.176520	8.057050e-11
1	Neuron 2	0.223748	1.243522e-16
2	Neuron 3	0.188780	3.427804e-12
3	Neuron 4	0.181770	2.141103e-11
4	Neuron 5	0.171539	2.731536e-10
5	Neuron 6	0.176845	7.430814e-11

(Figure 5: Visual Analysis – EME dataset. Real and Artificial)

Corrolation rate and p-Value from ORA (Real) Dataset

	Neuron	Correlation Coefficient	P-Value
0	Neuron 1	0.224446	1.039058e-07
1	Neuron 2	0.228586	5.941847e-08
2	Neuron 3	0.216543	2.931520e-07
3	Neuron 4	0.230389	4.642524e-08
4	Neuron 5	0.247409	4.084621e-09
5	Neuron 6	0.214529	3.795201e-07

Corrolation rate and p-Value from ORA (Artificial) Dataset

	Neuron	Correlation Coefficient	P-Value
0	Neuron 1	0.224446	1.039058e-07
1	Neuron 2	0.220537	1.743936e-07
2	Neuron 3	0.216543	2.931520e-07
3	Neuron 4	0.218077	2.404251e-07
4	Neuron 5	0.196753	3.330877e-06
5	Neuron 6	0.244373	6.387907e-09

(Figure 6: Visual Analysis – ORA dataset. Real and Artificial)

Discussion

The calculated firing rates for real and artificial spike trains demonstrated moderate correlations across both datasets, with higher correlations observed for neurons demonstrating distinct spiking patterns. The lower correlations may indicate the weaknesses of a simple LIF models, which may not adequately represent the intricate dynamics of real neurons, along with the variability in spike timing that artificial models omit [3].

Future enhancements may include the application of advanced neuron models, such as adaptive integrate-and-fire models or those that incorporate stochastic inputs, optimising input current stimuli to more accurately reflect real experimental conditions, and expanding evaluations via statistical metrics like mean squared error or cross-entropy loss [9].

IV. Third subsection of results

Decoding Behavioural Categories

This section aimed to decode the behavioural categories (ground truth in column 7) employing firing rates obtained from both real and artificial spike trains. The behavioural categories correspond to:

- **Class 1**: Correct choice (animal moves towards reward).
- **Classes 2-4**: Incorrect choices for different reasons.

Methodology

Six classification models were implemented for this task:

1. Logistic Regression:
2. Linear Discriminant analysis
3. Decision Tree Classifier.
4. K-neighbor Classifier.

5. Gaussian NB
6. SVM

The following machine learning models were compared with the accuracy score outputted from training with the firing rates from real and artificial neurons for both datasets visible in Appendix E and F.

Feature Preparation

Real neurons window size**:**

- EME dataset, the optimal window size was identified as 0.2 seconds.
- ORA dataset the optimal window size was identified as 0.18 seconds.

Artificial neurons window size**:**

- EME dataset, the optimal window size was identified as 0.3 seconds.
- ORA dataset the optimal window size was identified as 0.18 seconds.

Train-Test Splits: The datasets were split into 80% training and 20% testing subsets using.

Training method: The models were trained via the K-Fold Cross-Validation technique to guarantee thorough evaluation and prevent overfitting. This method entailed partitioning the dataset into K subsets, training the model on K-20 folds, then verifying it on the remaining fold. The procedure was executed K times, and the results were averaged to derive an accurate performance statistic.

Results

Dataset	Classifiers	Accuracy & error rate (Real Data)	Accuracy & error rate (Artificial data)
EME	Logistic Regression	Acc: 0.75 Err: 0.06	Acc: 0.63 Err: 0.06
EME	Linear Discriminant analysis	Acc: 0.74 Err: 0.06	Acc: 0.63 Err: 0.03
EME	Decision Tree Classifier.	Acc: 0.76 Err: 0.04	Acc: 0.63 Err: 0.06
EME	K-neighbor Classifier.	Acc: 0.77 Err: 0.05	Acc: 0.62 Err: 0.06
EME	Gaussian NB	Acc: 0.75 Err: 0.06	Acc: 0.62 Err: 0.06
EME	SVM	Acc: 0.77 Err: 0.04	Acc: 0.62 Err: 0.06

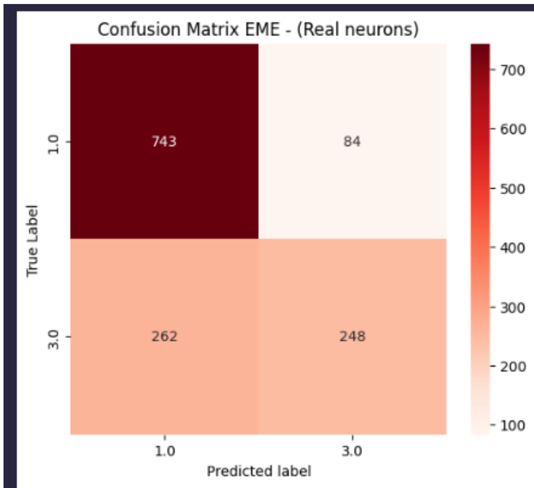
Table 1: Classifier accuracy results for real and artificial neurons for EME datasets

Dataset	Classifiers	Accuracy & error rate (Real Data)	Accuracy & error rate (Artificial data)
ORA	Logistic Regression	Acc: 0.75 Err: 0.10	Acc: 0.51 Err: 0.12
ORA	Linear Discriminant analysis	Acc: 0.75 Err: 0.10	Acc: 0.51 Err: 0.12
ORA	Decision Tree Classifier.	Acc: 0.78 Err: 0.10	Acc: 0.51 Err: 0.12
ORA	K-neighbor Classifier.	Acc: 0.76 Err: 0.10	Acc: 0.50 Err: 0.10
ORA	Gaussian NB	Acc: 0.73 Err: 0.11	Acc: 0.49 Err: 0.11
ORA	SVM	Acc: 0.78 Err: 0.09	Acc: 0.51 Err: 0.12

Table 2: Classifier accuracy results for real and artificial neurons for ORA datasets.

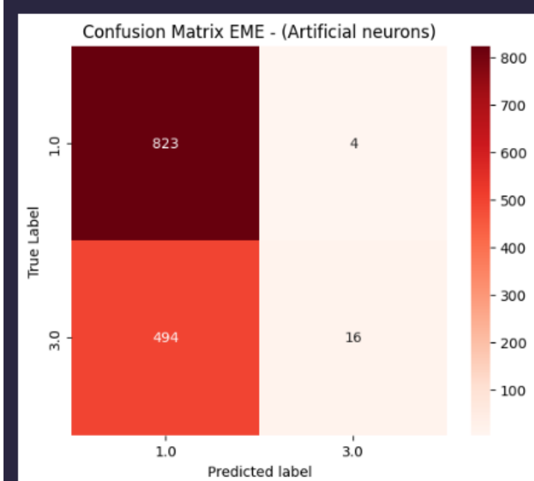
Selected Classifier:

Decision tree was the selected classifier to decode real neurons behaviors on both datasets. For the artificial neurons, the Decision tree model was used for EME, and the Gaussian classifier was used for ORA.




```
Accuracy Score: 0.7412116679132386

Classification Report
              precision    recall  f1-score   support

         1.0       0.74      0.90      0.81       827
         3.0       0.75      0.49      0.59       510

    accuracy                           0.74      1337
   macro avg       0.74      0.69      0.70      1337
weighted avg       0.74      0.74      0.73      1337

Selected model:  DecisionTreeClassifier() - Dataset name: EME - Real neurons
```

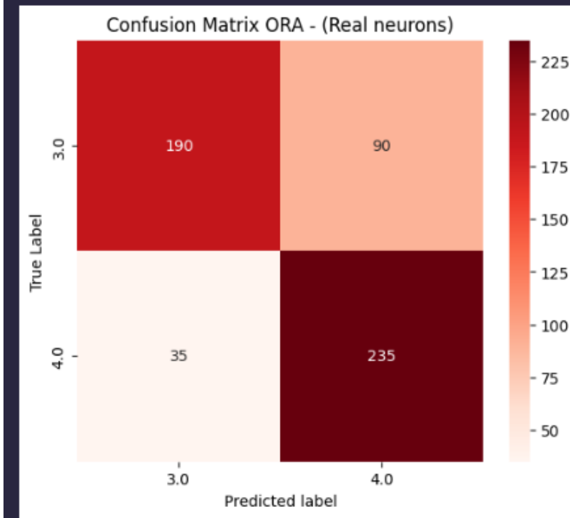
```
Selected model:  DecisionTreeClassifier() - Dataset name: EME - Artificial neurons
```




```
Accuracy Score: 0.6275243081525804

Classification Report
              precision    recall  f1-score   support

         1.0       0.62      1.00      0.77       827
         3.0       0.80      0.03      0.06       510

    accuracy                           0.63      1337
   macro avg       0.71      0.51      0.41      1337
weighted avg       0.69      0.63      0.50      1337
```

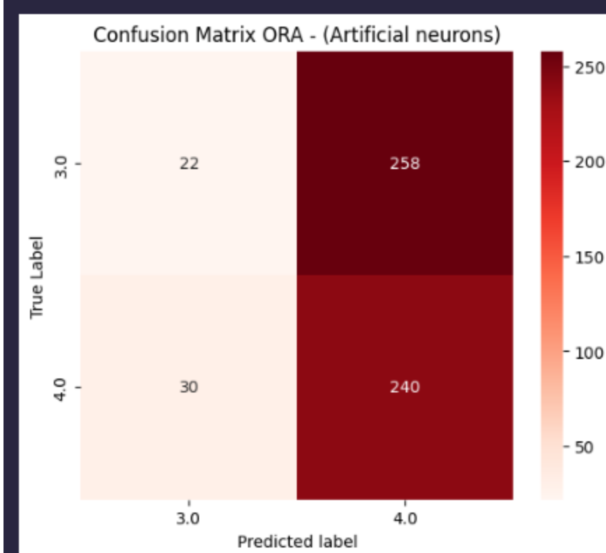
(Figure 7: Confusion matrices & classification report for EME dataset (real and artificial data) using Decision Tree Classifier)

```
Selected model:  DecisionTreeClassifier() - Dataset name: ORA - Real neurons
```




```
Accuracy Score: 0.7727272727272727

Classification Report
              precision    recall  f1-score   support

         3.0       0.84      0.68      0.75       280
         4.0       0.72      0.87      0.79       270

    accuracy                           0.77       550
   macro avg       0.78      0.77      0.77       550
weighted avg       0.78      0.77      0.77       550
```

```
Selected model:  GaussianNB() - Dataset name: ORA - Artificial neurons
```




```
Accuracy Score: 0.4763636363636364

Classification Report
              precision    recall  f1-score   support

         3.0       0.42      0.08      0.13       280
         4.0       0.48      0.89      0.62       270

    accuracy                           0.48       550
   macro avg       0.45      0.48      0.38       550
weighted avg       0.45      0.48      0.37       550
```

(Figure 8: Confusion matrices & classification report for ORA dataset (real and artificial data) using Decision Tree Classifier)

Discussion

Classifier Performance: The Decision Tree classifier consistently surpassed the other classifiers across both datasets. This indicates that the correlation between firing rates and behavioural categories may be non-linear and complex, benefiting from the decision tree approach [8].

Behavioral Categories: The study concentrates on the initial four trials, wherein EME contains two behavioural classes, 1 and 3, and ORA contains classes 3 and 4. The confusion matrices and classification reports indicate that the models effectively anticipate various behaviours when the firing rate is provided as input with the appropriate window size.

Real vs. Artificial Firing Rates: The lower performance associated with artificial firing rates suggests that our spike generation model (from Task 3) inadequately captures the complexities of real brain activity pertinent to behavioural decoding. Nonetheless, the ability to get over 50% accuracy with artificial rates indicates that the model effectively captures substantial behaviourally pertinent characteristics of the neural code. The confusion matrices for models trained with artificial neurons on both datasets indicate that the models effectively decode one class out of two.

Dataset Comparison: The EME dataset consistently demonstrated slightly better decoding accuracy relative to the ORA dataset. This indicates that the brain representations of behaviour may be more distinct or less noisy in the EME dataset, for the initial four trials.

The results indicate that behavioural categories can be decoded from the firing rates of simply six neurons with considerable accuracy. The disparity in performance between real and artificial firing rates highlights the necessity of accurately representing intricate temporal dynamics in neural models for behavioural decoding.

Conclusion & remarks

This work illustrates the viability of interpreting behavioural categories from the firing rates of a limited number of neurones with satisfactory precision. The efficacy of the decoding method emphasises the substantial information embedded in neuronal firing patterns, even with only six neurones. The study reveals several significant findings:

1. **Time window optimisation**: The 200ms interval for firing rate estimation consistently provided optimal decoding performance, indicating that this timescale encapsulates behaviourally pertinent brain dynamics.
2. **Classifier performance**: The exceptional performance of the Decision Tree classifier suggests that the relationship between brain activity and behaviour is probably non-linear and intricate.
3. **Artificial versus real spike trains**: Although the artificial spike generation model effectively captured notable characteristics of brain activity, the disparity in decoding performance indicates potential for enhancement in modelling fine-scale temporal correlations.
4. **Dataset-specific discrepancies**: The superior decoding accuracy for the ORA dataset relative to EME suggests possible variations in brain representations or noise levels between the two experimental settings.

These results hold significance for comprehending neural coding and advancing brain-computer interfaces. Future research should concentrate on enhancing spike production models to accurately represent fine-scale temporal dynamics and investigating advanced decoding algorithms that can utilise the intricate, non-linear correlations present in brain data.

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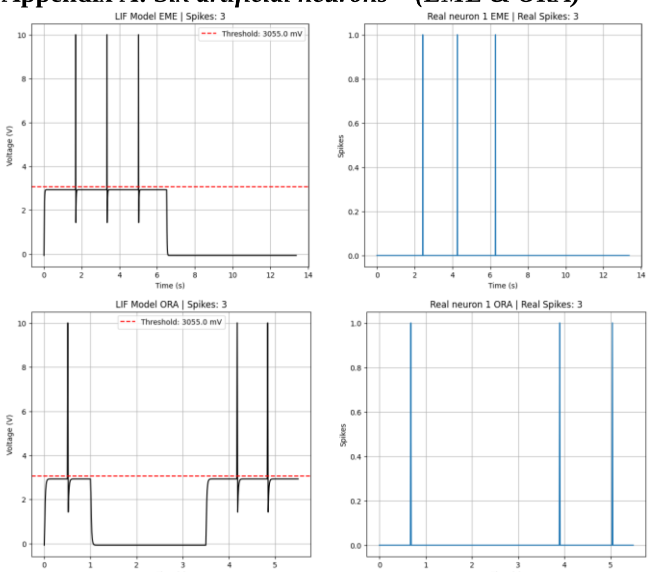
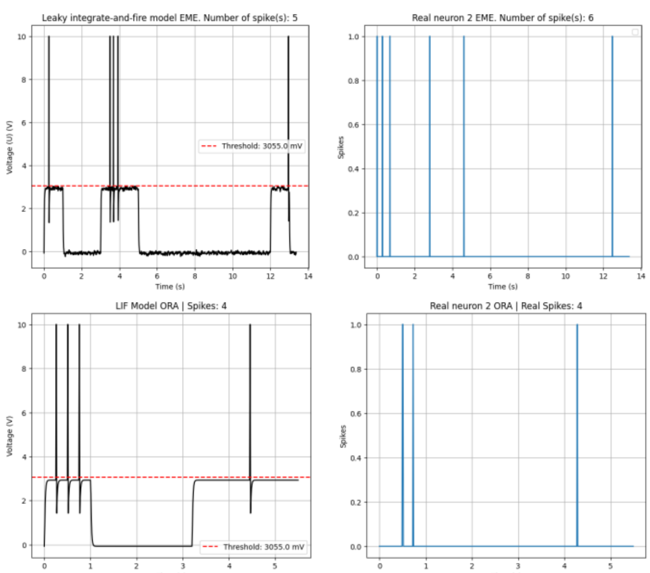
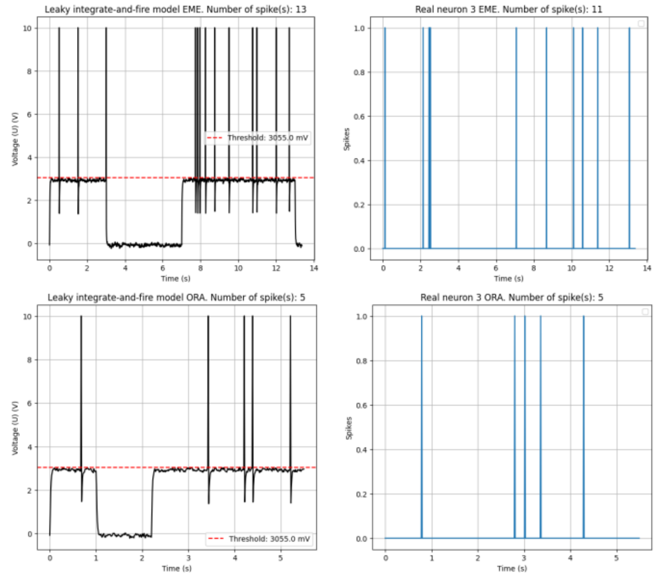
Appendix A: *Six artificial neurons – (EME & ORA)*



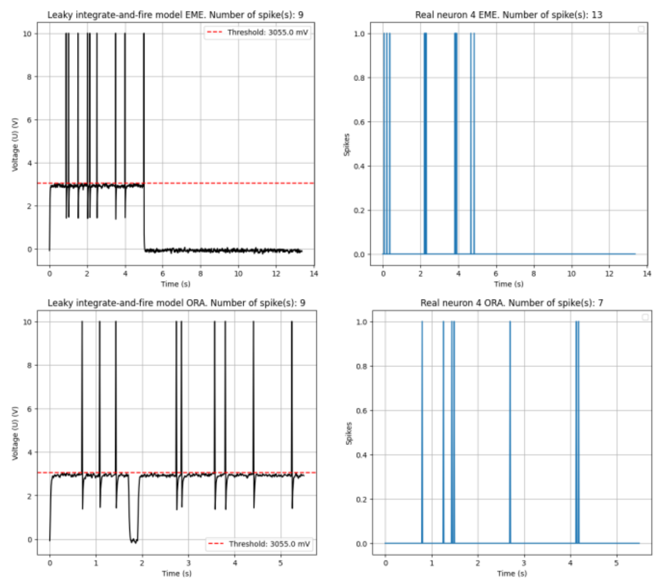
(Artificial neuron 1)



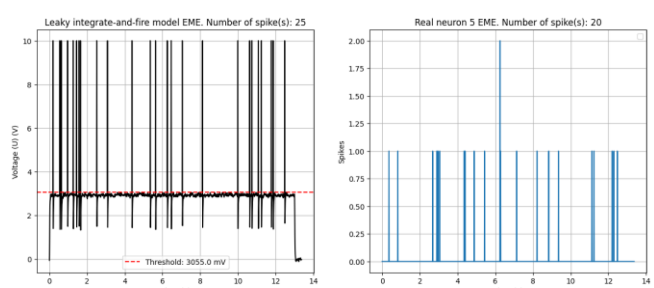
(Artificial neuron 2)

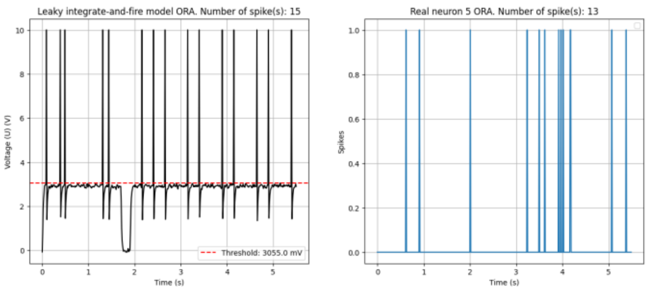


(Artificial neuron 3)

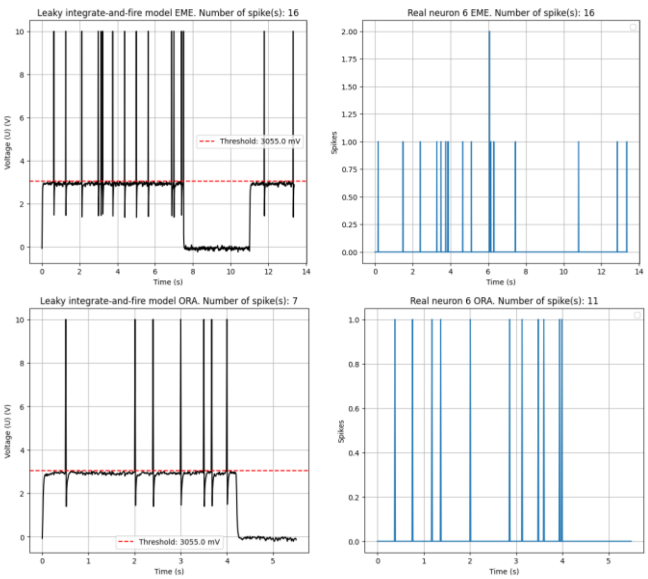


(Artificial neuron 4)



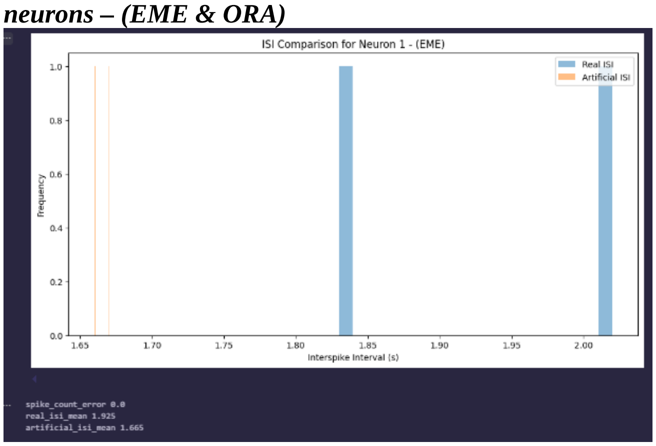


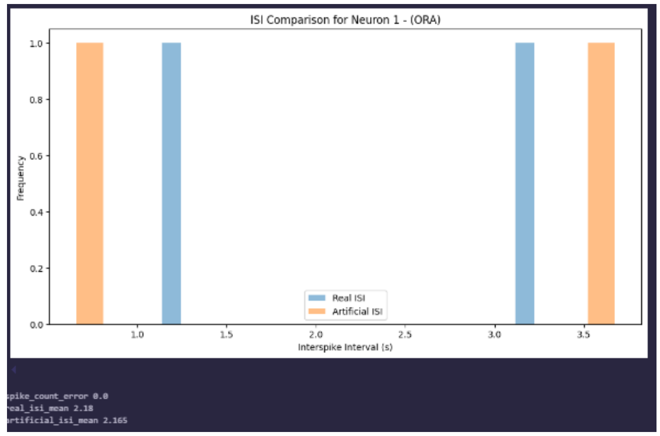
(Artificial neuron 5)



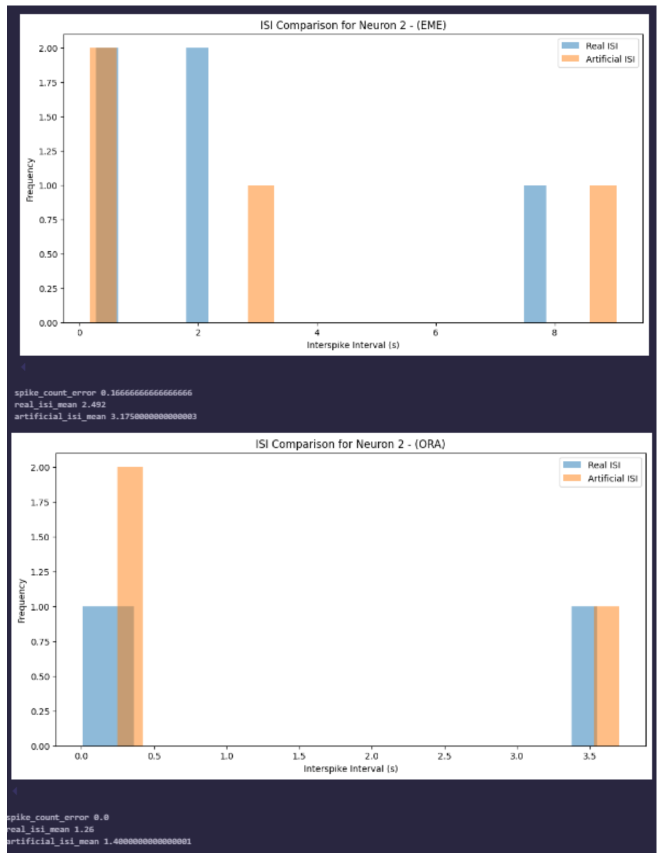
(Artificial neuron 6)

Appendix B: ***ISI distribution & spike count error for all neurons – (EME & ORA)***

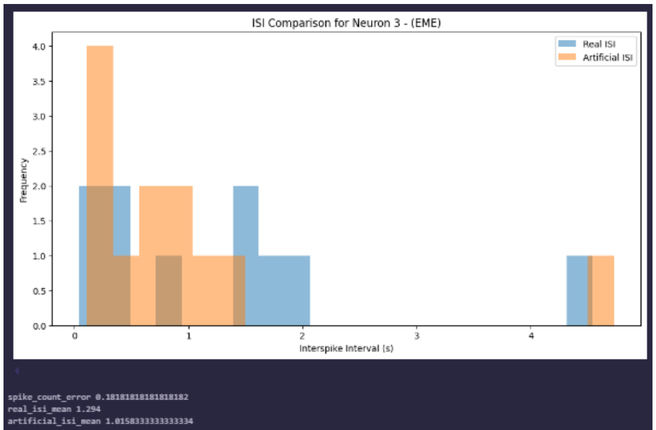


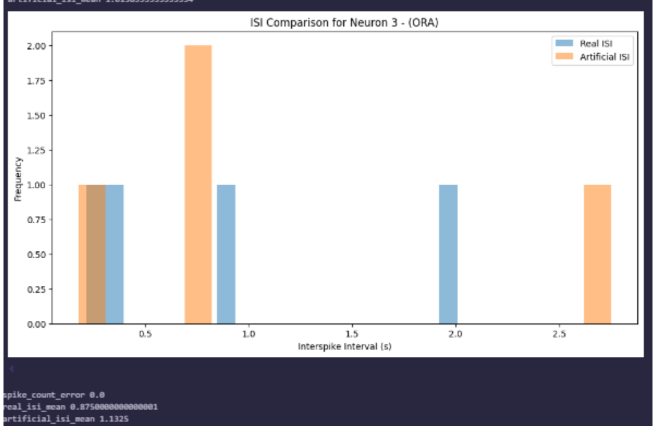


(Neuron 1)

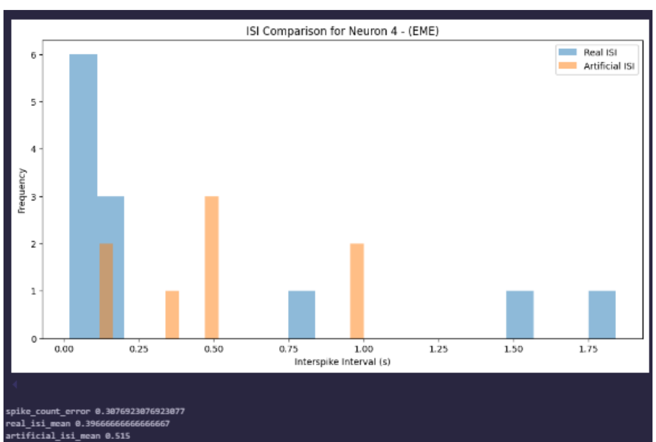


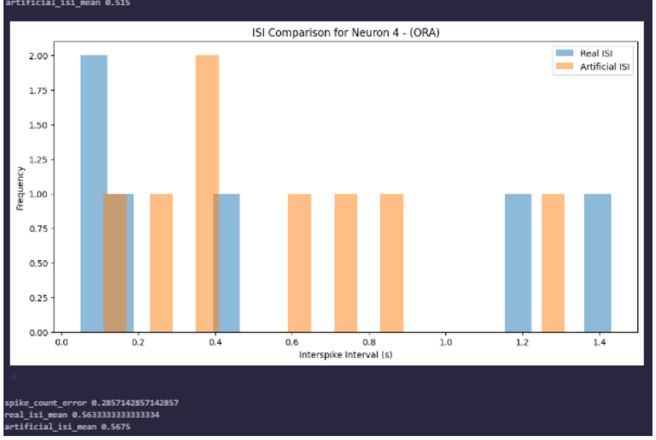
(Neuron 2)



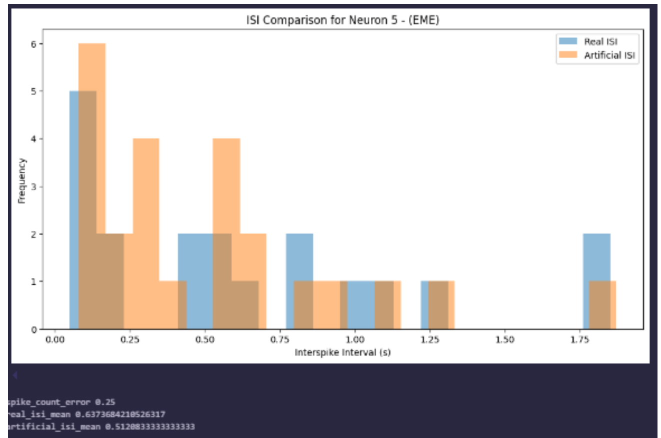


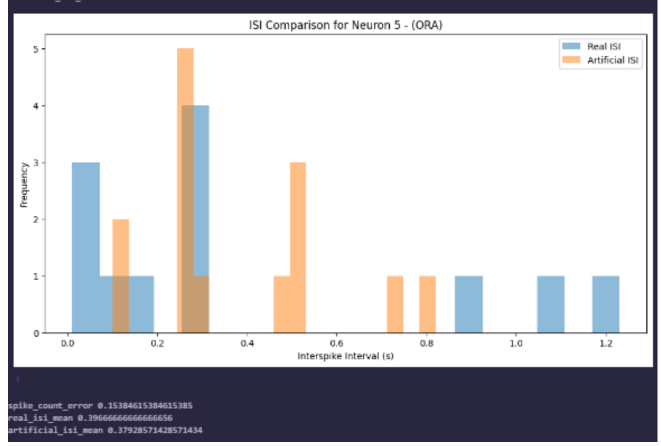
(Neuron 3)



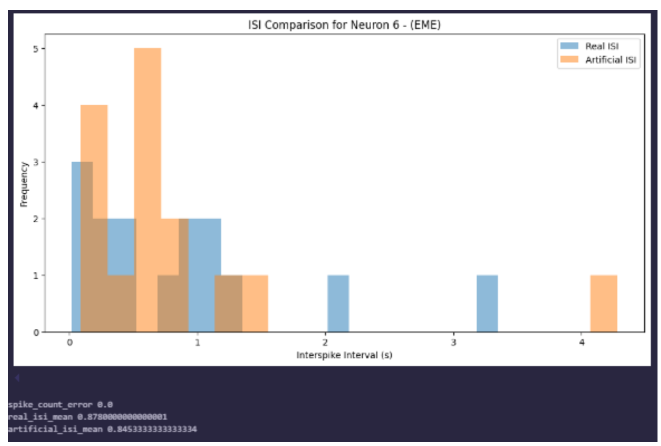


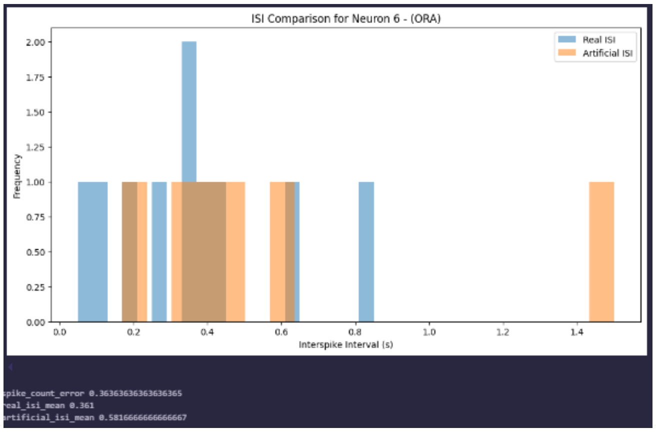
(Neuron 4)





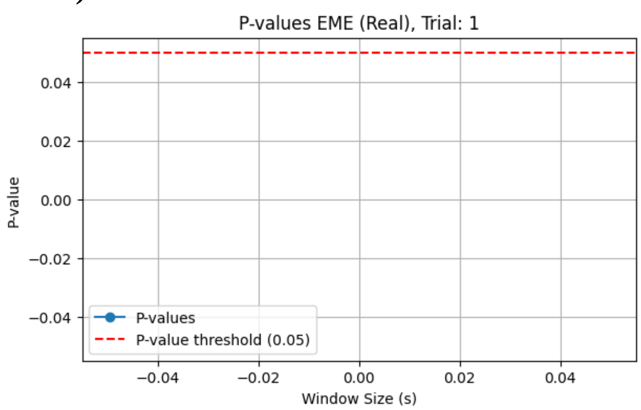
(Neuron 5)

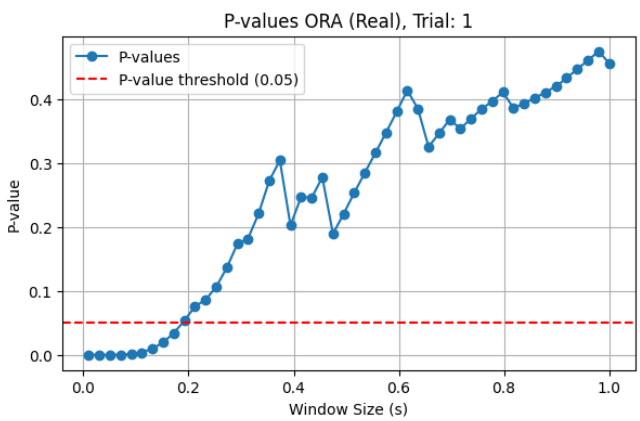




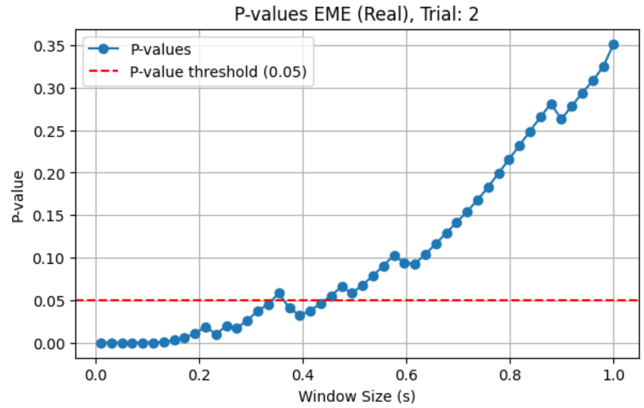
(Neuron 6)

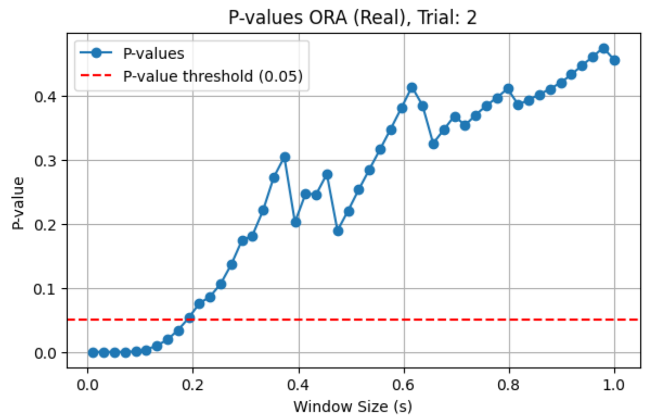
Appendix C: ***Window size analysis for Real dataset– (EME & ORA)***



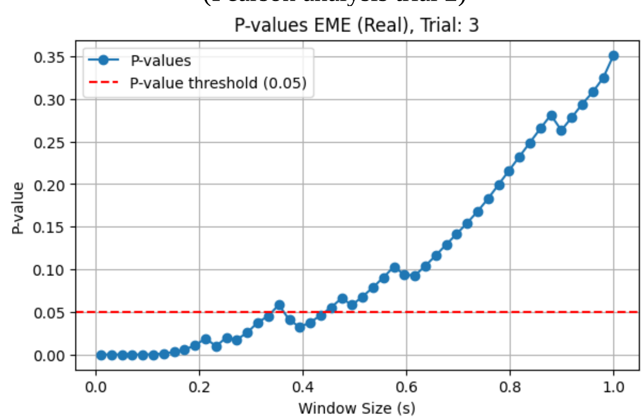


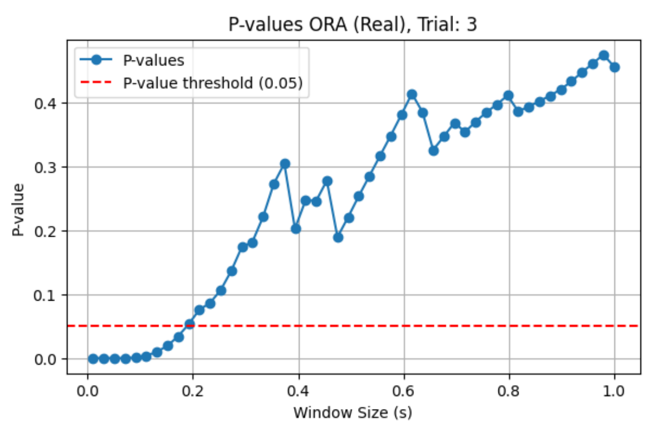
(Pearson analysis trial 1)



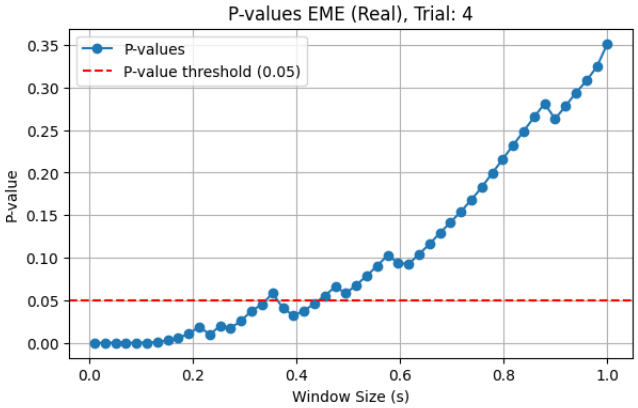


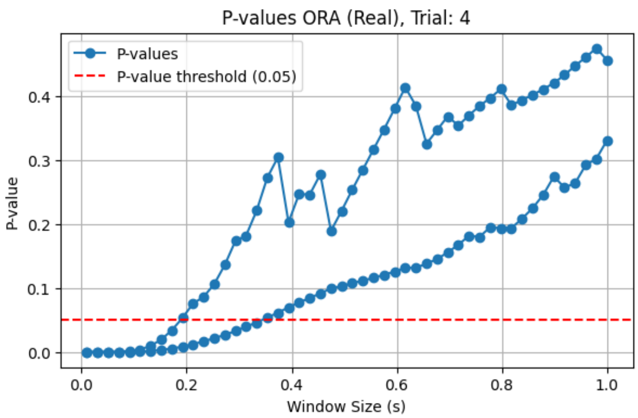
(Pearson analysis trial 2)





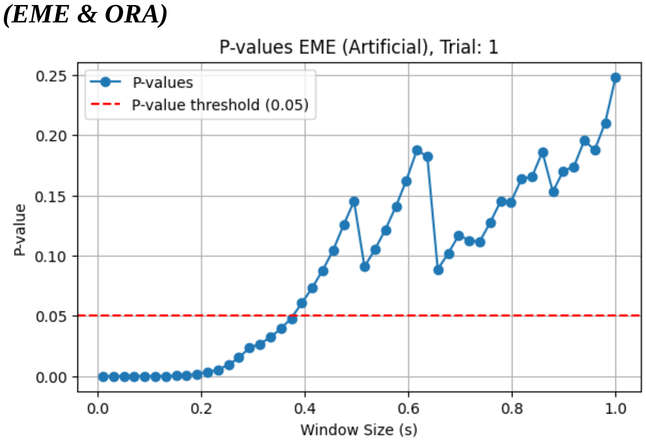
(Pearson analysis trial 3)

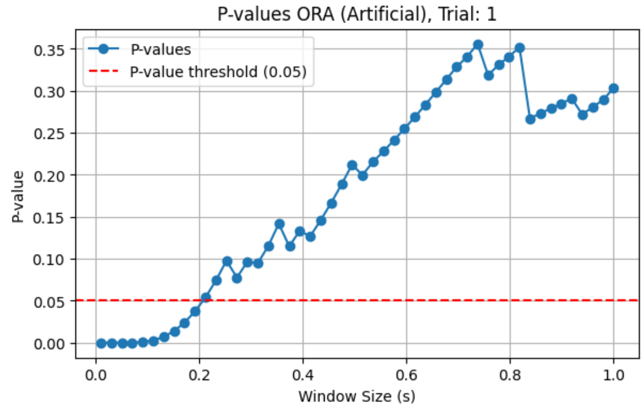




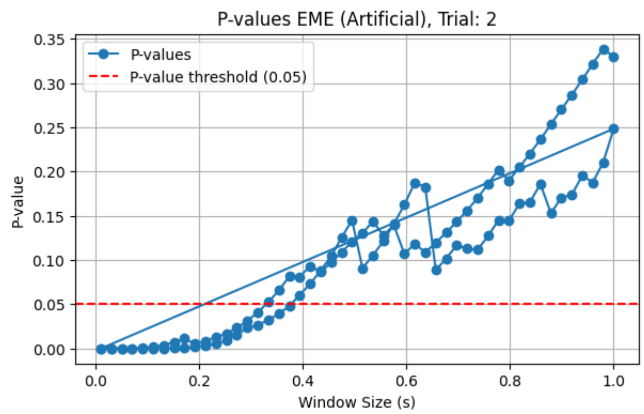
(Pearson analysis trial 4)

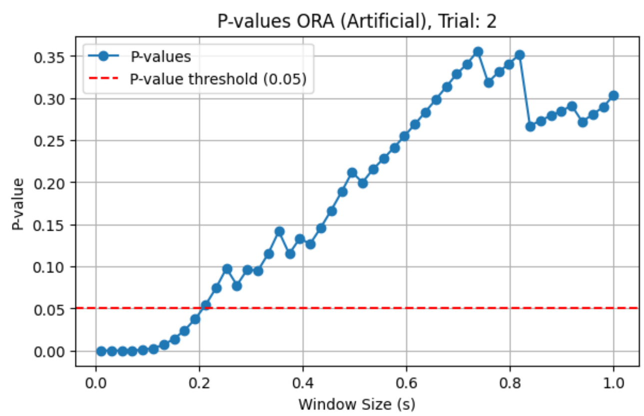
Appendix D: ***Window size analysis for Artificial dataset– (EME & ORA)***



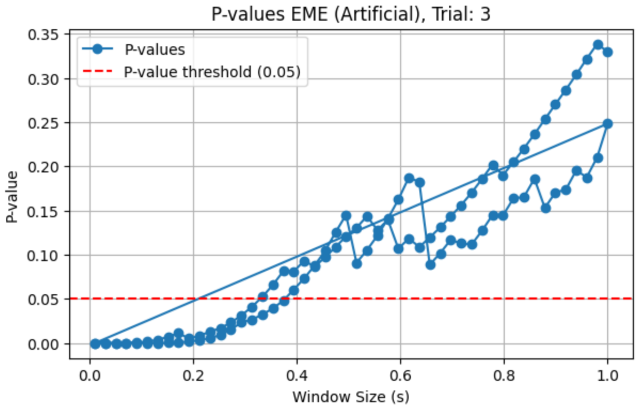


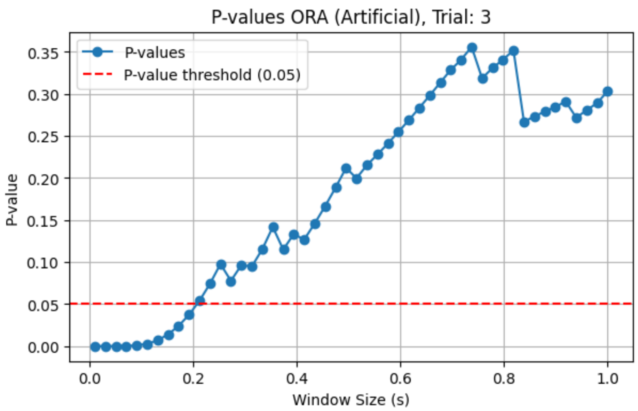
(Pearson analysis trial 1)



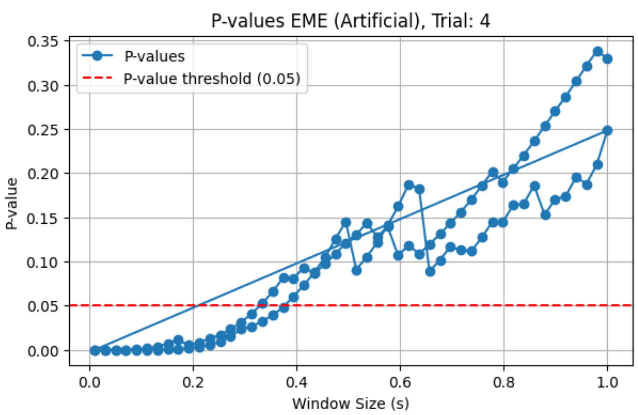


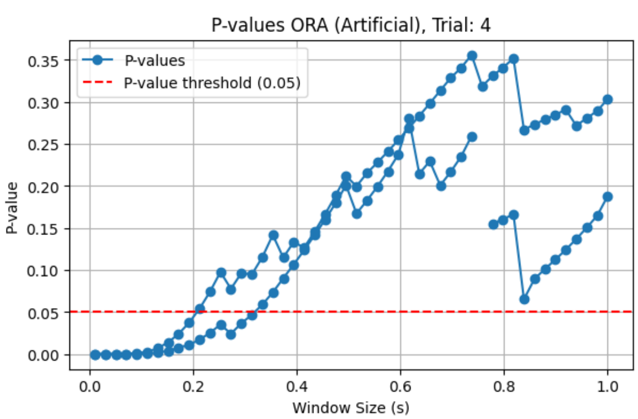
(Pearson analysis trial 2)





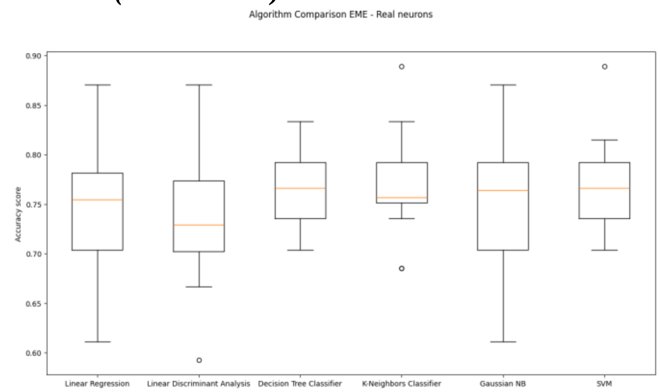
(Pearson analysis trial 3)

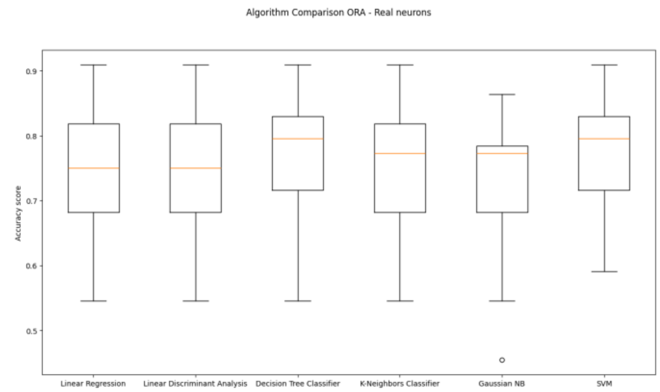




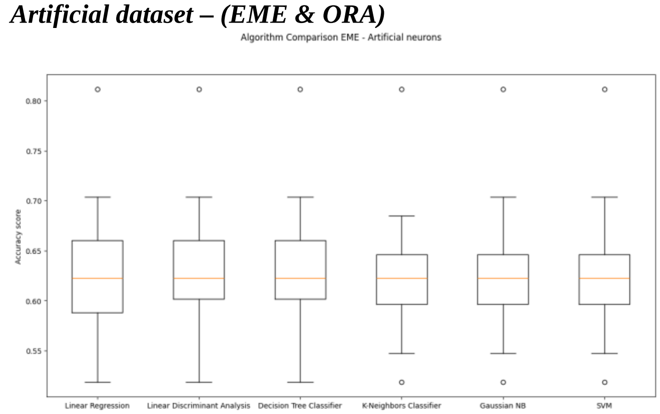
(Pearson analysis trial 4)

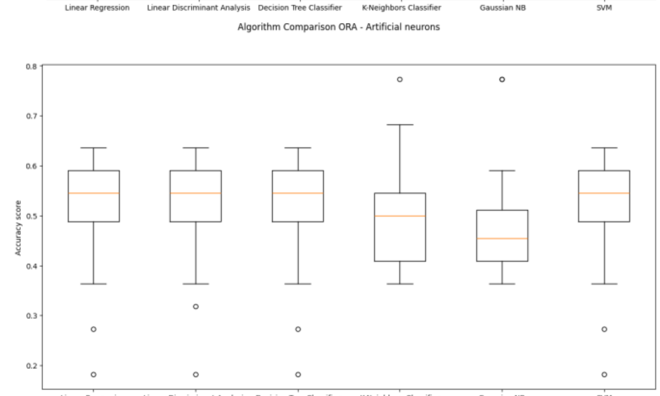
Appendix E: Machine learning models comparison - *Real dataset – (EME & ORA)*





Appendix F: Machine learning models comparison - *Artificial dataset – (EME & ORA)*





Appendix G: *Project python code:*

```
# %% [markdown]
# ## Imports and setting variables

# %%
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from dataclasses import dataclass, field
from typing import TYPE_CHECKING
import matplotlib.gridspec as gridspec
if TYPE_CHECKING:
   from numpy.typing import NDArray

from scipy.stats import pearsonr
import warnings

# %%
EME = np.loadtxt('DataSetCoursework_EME.txt')
ORA = np.loadtxt('DataSetCoursework_ORA.txt')

# %%
Spikes_EME = EME[:, :-2] # Column 1 to 6
ground_tr_EME = EME[:, -2] # Column 7
Trials_EME = EME[:, -1] # Column 8

Spikes_ORA = ORA[:, :-2] # Column 1 to 6
ground_tr_ORA = ORA[:, -2] # Column 7
Trials_ORA = ORA[:, -1] # Column 8

# %% [markdown]
# ## Estimate firing rate

# %% [markdown]
# #### Calculate the firing rate:
# $$r = \frac {n(spikes\space per\space trials)}{T (total\space trial\space duration)} $$

# %%
warnings.simplefilter('ignore')
@dataclass
class Fire_Rate_Estimation:
   spikes: 'NDArray'
   trials: 'NDArray'
   dataset_name: str
   bin_size: float = field(init=False, default=.01)

   def Calculate_rate(self, window_size):

      try:
         n, m = self.spikes.shape
      except ValueError as e:
         n = self.spikes.shape[0]
         m = 1

      window_steps = int(window_size / self.bin_size)
      Rate = np.zeros_like(self.spikes)

      # Iterate over neurons and calculate firing rates
      for j in range(m):
         Smothed = []
         for i in range(n - window_steps + 1):
            spike_one_neuron = self.spikes[i: i + window_steps, j]
            rate_in_this_window = (np.sum(spike_one_neuron) / window_size) # Calculating the firing rate in each time window
            Smothed.append(rate_in_this_window)
         Smothed.extend([Smothed[-1]] * (window_steps - 1))
         Rate[:, j] = Smothed

      Rate = np.hstack((Rate, self.trials[:, np.newaxis])) # Adding the trials column to the Rate matrix

      return Rate

   def display_aggregated_plot(self, rate):
      n_1, neurons = self.spikes.shape
      times = np.arange(0, (n_1 - 1) * self.bin_size + self.bin_size, self.bin_size)

      fig, axs = plt.subplots(neurons, 2, figsize=(15, 8))
      fig.suptitle(f"Firing rate from {self.dataset_name} dataset")
      for j in range(neurons):
         axs[j, 0].plot(times, self.spikes[:, j])
         axs[j, 0].set_title(f'Neuron {j + 1}')
         axs[j, 0].set_ylabel('Spikes')
         axs[j, 0].set_xlabel('Time (s)')

         axs[j, 1].plot(times, rate[:, j], 'r')
         axs[j, 1].set_title(f'Neuron {j + 1} rate')
         axs[j, 1].set_ylabel('Hz')
         axs[j, 1].set_xlabel('Time (s)')

      # plt.title("sdf")
      fig.tight_layout()
      plt.show()

   def display_trial_plot(self, rate, trial_num: int, selected_neuron: int):
      n_1, neurons = self.spikes.shape
      times = np.arange(0, (n_1 - 1) * self.bin_size + self.bin_size, self.bin_size)

      if trial_num + 1 > int(max(self.trials)) + 1:
         trial_num = int(max(self.trials)) + 1

      # for j in range(neurons):
      for i in range(1, trial_num + 1):
```

```
        trial_index = (self.trials == i)
        # print("analysis: ",len(times[:len(self.spikes[trial_index, j])]), len(self.spikes[trial_index, j]))
        fig, axs = plt.subplots(1, 2, figsize=(20, 2))
        fig.suptitle(f"Firing rate from {self.dataset_name} dataset")
        axs[0].plot(times[:len(self.spikes[trial_index, selected_neuron - 1])], self.spikes[trial_index, selected_neuron - 1])
        axs[0].set_title(f'Neuron {selected_neuron}, trial: {i}')
        axs[0].set_ylabel('Spikes')
        axs[0].set_xlabel('Time (s)')

        axs[1].plot(times[:len(self.spikes[trial_index, selected_neuron - 1])], rate[trial_index, selected_neuron - 1], 'r')
        axs[1].set_title(f'Neuron {selected_neuron} rate, trial: {i}')
        axs[1].set_ylabel('Hz')
        axs[1].set_xlabel('Time (s)')

      # plt.title("sdf")
      plt.tight_layout()
      plt.show()


    def Calculate_corrolation_coef(self, rate):
      print(f"Corrolation rate and p-Value from {self.dataset_name} Dataset")
      # Correlation coefficients between spike trains and rates
      # print('*********************************')
      # print('CORRELATION COEFFICIENTS RATE vs SPIKES (p value). Significance: p<0.05')
      # print('*********************************')
      _, neurons = self.spikes.shape

      all_trails_corr = []
      all_trails_p_value = []
      all_trails_neurons = []

      for j in range(neurons):
        for i in range(1, int(max(self.trials)) + 1):
          trial_index = (self.trials == i)
          current_trial_rates = rate[trial_index, j]
          current_trial_spikes = self.spikes[trial_index, j]
          corr_value, p = pearsonr(current_trial_rates, current_trial_spikes)
          # print(f'Trial {i} Neuron {j + 1} correlation = {corr_value} ({p})')
        current_rates = rate[:, j]
        current_spikes = self.spikes[:, j]
        corr_value, p = pearsonr(current_rates, current_spikes)

        all_trails_corr.append(corr_value)
        all_trails_p_value.append(p)
        all_trails_neurons.append(f"Neuron {j + 1}")
        # print('*********************************')
        # print(f'All trials Neuron {j + 1} correlation = {corr_value} ({p})')
        # print('*********************************')

      return pd.DataFrame({'Neuron': all_trails_neurons, 'Correlation Coefficient': all_trails_corr, 'P-Value': all_trails_p_value})

# %% [markdown]
# ## Finding the optimal windows size

# %% [markdown]
# - Using two metrics to find the

# %%
@dataclass
class Find_optimal_window:
    window_start: float
    window_stop: float|int
    ds: 'NDArray'
    ds_trials: 'NDArray'
    ds_name: str


    def _Calculate_rate(self, window_size, bin_size=.01):

      try:
        n, m = self.ds.shape
      except ValueError as e:
        n = self.ds.shape[0]
        m = 1

      window_steps = int(window_size / bin_size)
      Rate = np.zeros_like(self.ds)

      # Iterate over neurons and calculate firing rates
      for j in range(m):
        Smothed = []
        for i in range(n - window_steps + 1):
          spike_one_neuron = self.ds[i: i + window_steps, j]
          rate_in_this_window = (np.sum(spike_one_neuron) / window_size) # Calculating the firing rate in each time window
          Smothed.append(rate_in_this_window)
        Smothed.extend([Smothed[-1]] * (window_steps - 1))
        Rate[:, j] = Smothed

      Rate = np.hstack((Rate, self.ds_trials[:, np.newaxis])) # Adding the trials column to the Rate matrix

      return Rate

    def sliding_window(self, verbose=True):
      window_sizes = np.linspace(self.window_start, self.window_stop)
      _, num_neurons = self.ds.shape
```

```
        window_size_arr = []
        p_values = []
        r_squared_values = []

        # Loop through window sizes
        for win_size in window_sizes:
            current_rate =
self._Calculate_rate(window_size=win_size)
            p_val_sum = 0
            r2_sum = 0

            # Evaluate all neurons
            for neuron in range(num_neurons):

                rate = current_rate[:, neuron]
                spikes = self.ds[:, neuron]

                # for i in range(1, int(max(self.ds_trials)) + 1):
                #     trial_index = (self.ds_trials == i)
                #     current_trial_rates = current_rate[trial_index,
neuron]
                #     current_trial_spikes = self.ds[trial_index,
neuron]
                #     corr_value, p = pearsonr(current_trial_rates,
current_trial_spikes)

                # Compute correlation and p-value
                corr_coef, p_value = pearsonr(rate, spikes)
                p_val_sum += p_value

                # Compute R^2
                residuals = spikes - rate
                ss_res = np.sum(residuals**2)
                ss_tot = np.sum((spikes - np.mean(spikes))**2)
                r2 = 1 - (ss_res / ss_tot)
                r2_sum += r2

            # Average metrics across neurons
            avg_p_value = p_val_sum / num_neurons
            # avg_p_value = p_val_sum
            avg_r_squared = r2_sum / num_neurons

            window_size_arr.append(win_size)
            p_values.append(avg_p_value)
            r_squared_values.append(avg_r_squared)

        if verbose:
            # self.p_value_evolution(window_size_arr, p_values)
            # self.r_square_evolution(window_size_arr,
r_squared_values)
            fig = plt.figure(figsize=(18, 10))
            gs = gridspec.GridSpec(1, 2)

            # P-value plot shwing the evolution of p-value across
different windows sizes
            ax1 = fig.add_subplot(gs[0])
            ax1.plot(window_size_arr, p_values, label="P-
values", marker='o')
            ax1.axhline(0.05, color='red', linestyle='--', label="P-
value threshold (0.05)")
            ax1.set_title(f"Evolution of P-values {self.ds_name}")
            ax1.set_xlabel("Window Size (s)")
            ax1.set_ylabel("P-value")
            ax1.legend()
            ax1.grid()

            # R^2 plot showing the evolution of the R square value
with different window sizes
            ax2 = fig.add_subplot(gs[1])
            ax2.plot(window_size_arr, r_squared_values,
label="R^2 Values", marker='x')
            ax2.set_title(f"Evolution of R square with Window
Size {self.ds_name}")
            ax2.set_xlabel("Window Size (s)")
            ax2.set_ylabel("R square Value")
            ax2.legend()
            ax2.grid()

    def sliding_window_trial(self, trial_num: int,
verbose=True):
        window_sizes = np.linspace(self.window_start,
self.window_stop)
        _, num_neurons = self.ds.shape

        window_size_arr = []
        p_values = []
        r_squared_values = []
        p_val_sum = 0
        r2_sum = 0


        for i in range(1, trial_num + 1):
            trial_index = (self.ds_trials == i)

            for win_size in window_sizes:
                current_rate =
self._Calculate_rate(window_size=win_size)
                p_val_sum = 0
                r2_sum = 0

                for neuron in range(num_neurons):

                    current_trial_rates = current_rate[trial_index,
neuron]
                    current_trial_spikes = self.ds[trial_index, neuron]
                    corr_value, p = pearsonr(current_trial_rates,
current_trial_spikes)
                    p_val_sum += p

                avg_p_value = p_val_sum / num_neurons
                window_size_arr.append(win_size)
                p_values.append(avg_p_value)
```

```
        if verbose:
            # self.p_value_evolution(window_size_arr, p_values)
            # self.r_square_evolution(window_size_arr, r_squared_values)
            fig = plt.figure(figsize=(15, 4))
            gs = gridspec.GridSpec(1, 2)

            # P-value plot shwing the evolution of p-value across different windows sizes
            ax1 = fig.add_subplot(gs[0])
            ax1.plot(window_size_arr, p_values, label="P-values", marker='o')
            ax1.axhline(0.05, color='red', linestyle='--', label="P-value threshold (0.05)")
            ax1.set_title(f"P-values {self.ds_name}, Trial: {i}")
            ax1.set_xlabel("Window Size (s)")
            ax1.set_ylabel("P-value")
            ax1.legend()
            ax1.grid()

            # R^2 plot showing the evolution of the R square value with different window sizes
            # ax2 = fig.add_subplot(gs[1])
            # ax2.plot(window_size_arr, r_squared_values, label="R^2 Values", marker='x')
            # ax2.set_title(f"Evolution of R square with Window Size {self.ds_name}")
            # ax2.set_xlabel("Window Size (s)")
            # ax2.set_ylabel("R square Value")
            # ax2.legend()
            # ax2.grid()

# %%
Optimal_win_size_EME = Find_optimal_window(ds=Spikes_EME, ds_trials=Trials_EME,window_start=.01, window_stop=1, ds_name="EME (Real)")
Optimal_win_size_ORA = Find_optimal_window(ds=Spikes_ORA, ds_trials=Trials_ORA, window_start=.01, window_stop=1, ds_name="ORA (Real)")

# %% [markdown]
# ##### Trial by trial analysis

# %%
Optimal_win_size_EME.sliding_window_trial(trial_num=4)

# %%
Optimal_win_size_ORA.sliding_window_trial(trial_num=4)

# %% [markdown]
# ## Display neurons rate and correlations

# %%
Firing_Rate_EME = Fire_Rate_Estimation(spikes=Spikes_EME, trials=Trials_EME, dataset_name="EME (Real)")
Firing_Rate_ORA = Fire_Rate_Estimation(spikes=Spikes_ORA, trials=Trials_ORA, dataset_name="ORA (Real)")

# %%
rate_EME = Firing_Rate_EME.Calculate_rate(window_size=.2)
rate_ORA = Firing_Rate_ORA.Calculate_rate(window_size=.18)

# %%
Firing_Rate_EME.display_aggregated_plot(rate_EME)
Firing_Rate_ORA.display_aggregated_plot(rate_ORA)

# %% [markdown]
# ### Neural rate for first 4 trials

# %%
selected_trials = 4
trial_index = (Trials_EME <= selected_trials) # First 4 trials
trial_index_ORA = (Trials_ORA <= selected_trials) # First 4 trials

temp_spikes_EME = []
temp_spikes_ORA =  []

for neuron in Spikes_EME.T:
   temp_spikes_EME.append(neuron[trial_index])

for neuron in Spikes_ORA.T:
   temp_spikes_ORA.append(neuron[trial_index_ORA])

# %%
__Firing_Rate_EME = Fire_Rate_Estimation(spikes=np.array(temp_spikes_EME).T, trials=Trials_EME[trial_index], dataset_name="EME (Real)")
__Firing_Rate_ORA = Fire_Rate_Estimation(spikes=np.array(temp_spikes_ORA).T, trials=Trials_ORA[trial_index_ORA], dataset_name="ORA (Real)")

__rate_EME = __Firing_Rate_EME.Calculate_rate(window_size=.2)
__rate_ORA = __Firing_Rate_ORA.Calculate_rate(window_size=.18)

# %%
__Firing_Rate_EME.display_aggregated_plot(__rate_EME)
__Firing_Rate_ORA.display_aggregated_plot(__rate_ORA)

# %%
__Firing_Rate_EME.Calculate_corrolation_coef(__rate_EME)
```

```
# %%
__Firing_Rate_ORA.Calculate_corrolation_coef(__rate_ORA
)

# %% [markdown]
# ## Generating Artificial Spike Trains

# %%
from dataclasses import dataclass, field
import numpy as np
import matplotlib.pyplot as plt
from typing import Any

@dataclass
class Neuron_Network_test:
    input_currents: 'np.ndarray'
    spikes: 'np.ndarray'
    trials: 'np.ndarray'
    ds_name: str
    bin_size: float = field(init=False, default=0.01)
    dataset: 'np.ndarray'

    def leaky_if_1(self, selected_trial, selected_neuron,
duration=0.8, verbose=True, dt=0.0001):

        # Fixed parameters
        tau = 0.020  # Membrane time constant (s)
        R = 5e7  # Membrane resistance (Ohms)
        U_rest = -0.07  # Resting potential (V)
        theta = 3.055  # Threshold potential for spike (V)
        spike_volt = 10  # Voltage during spike (V)

        # Input currents setup
        if self.input_currents is None:
            raise ValueError("Input currents must be provided.")
        else:
            psc = self.input_currents[:]  # Times of excitatory
currents
        U_0 = 0.3
        I_0 = U_0 / R  # Input current (A)

        # Initialization
        index_pscs = np.round(psc / dt).astype(int)  # Indices of
pulse times
        n_steps = int(duration / dt)  # Number of simulation steps
        U = np.zeros(n_steps + 1)  # Membrane potential array
        U_plot = np.zeros(n_steps + 1)  # Membrane potential
for plotting
        U[0] = U_rest  # Initialize with resting potential
        U_plot[0] = U_rest
        I = np.zeros(n_steps + 1)  # Input current array
        time = np.linspace(0, duration, n_steps + 1)  # Time
array
        n_spikes = 0  # Spike counter

        # Simulation
        for i in range(n_steps):
            for k in range(len(psc)):
                if i == index_pscs[k]:
                    I[i] += I_0
            dU = (dt / tau) * (U_rest - U[i] + I[i] * R)
            U[i + 1] = U[i] + dU
            U_plot[i + 1] = U[i + 1]

            # Spike detection
            if U[i + 1] > theta:
                U_plot[i + 1] = spike_volt
                U[i + 1] = U_rest
                n_spikes += 1

        if verbose:
            n_1, neurons = self.dataset.shape
            times = np.arange(0, (n_1 - 1) * self.bin_size +
self.bin_size, self.bin_size)
            trial_index = (self.trials <= selected_trial)

            # Plotting
            fig, axs = plt.subplots(1, 2, figsize=(15, 6))
            axs[0].plot(time, U_plot, color='black')
            axs[0].axhline(y=theta, color='red', linestyle='--',
label=f'Threshold: {theta * 1000:.1f} mV')
            axs[0].set_title(f'LIF Model {self.ds_name} | Spikes:
{n_spikes}')
            axs[0].set_xlabel('Time (s)')
            axs[0].set_ylabel('Voltage (V)')
            axs[0].grid(True)
            axs[0].legend()

            axs[1].plot(times[:len(self.dataset[trial_index,
selected_neuron - 1])],
                        self.dataset[trial_index, selected_neuron - 1])
            axs[1].set_title(f'Real neuron {selected_neuron}
{self.ds_name} | Real Spikes:
{len(np.where(self.dataset[trial_index, selected_neuron - 1]
== 1)[0])}')
            axs[1].set_ylabel('Spikes')
            axs[1].set_xlabel('Time (s)')
            axs[1].grid(True)
            plt.show()

            self.evaluate_similarity(selected_trial=selected_trial,
selected_neuron=selected_neuron,
art_neuron_output=U_plot, threshold=theta)


        return time, U_plot

    def leaky_if_2(self, selected_trial, selected_neuron,
duration=0.2, dt=0.0001, arp=0.06, verbose=True):
        # Fixed parameters
        tau = 0.020  # Membrane time constant (s)
        R = 3e7  # Membrane resistance (Ohms)
        U_rest = -0.07  # Resting potential (V)
```

```python
        theta = 3.055  # Threshold potential for spike (V)
        spike_volt = 10  # Voltage during spike (V)

        psc = self.input_currents[:]  # Times of excitatory currents
        U_0 = 0.3
        I_0 = U_0 / R  # Input current (A)
        # I_0 = 1e-8  # Input current (A)

        # Initialization
        # arp = 0.060

        background = 3e-9

        index_pscs = np.round(psc / dt).astype(int)  # Indices of pulse times
        n_steps = int(duration / dt)  # Number of simulation steps
        U = np.zeros(n_steps + 1)  # Membrane potential array
        U_plot = np.zeros(n_steps + 1)  # Membrane potential for plotting
        U[0] = U_rest  # Initialize with resting potential
        U_plot[0] = U_rest
        I = np.zeros(n_steps + 1)  # Input current array
        time = np.linspace(0, duration, n_steps + 1)  # Time array
        n_spikes = 0  # Spike counter
        t_spike = 0 # Addition with respect to LeakyIF_1: Intial time since last spike -will be used in the implementation of the refractory period

        # Background noise drawn from a normal distribution (central limit)
        randI = background * np.random.randn(1, n_steps)

        # Simulation
        # print(randI)
        for i in range(n_steps):
            # if i >= 500 and i <= 1200:
            #     continue
            for k in range(len(psc)):
                if i == index_pscs[k]:
                    I[i] += I_0


            dU = (dt / tau) * (U_rest - U[i] + I[i] * R + randI[0][i] * R)
            U[i + 1] = U[i] + dU
            U_plot[i + 1] = U[i + 1]

            # Spike detection
            if U[i + 1] > theta:
                # theta += .0001
                if n_spikes > 0:
                    if time[i] >= (t_spike + arp):
                        U_plot[i + 1] = spike_volt
                        U[i + 1] = U_rest
                        n_spikes += 1
                    else:
                        U[i + 1] = U[i]
                        U_plot[i + 1] = U[i + 1]
                else:
                    U_plot[i + 1] = spike_volt
                    U[i + 1] = U_rest
                    t_spike = time[i]
                    n_spikes += 1

        if verbose:
            n_1, neurons = self.dataset.shape
            times = np.arange(0, (n_1 - 1) * self.bin_size + self.bin_size, self.bin_size)
            trial_index = (self.trials <= selected_trial)
            # Plotting
            fig, axs = plt.subplots(1, 2, figsize=(15, 6))
            axs[0].plot(time, U_plot, color='black')
            axs[0].axhline(y=theta, color='red', linestyle='--', label=f'Threshold: {theta * 1000:.1f} mV')
            axs[0].set_title(f'Leaky integrate-and-fire model {self.ds_name}. Number of spike(s): {n_spikes}')
            axs[0].set_xlabel('Time (s)')
            axs[0].set_ylabel('Voltage (U) (V)')
            axs[0].grid(True)
            axs[0].legend()
            # print(self.dataset[selected_trial, selected_neuron - 1])
            # axs[1].eventplot(np.where(self.spikes == 1)[0] * dt, color='black')
            axs[1].plot(times[:len(self.dataset[trial_index, selected_neuron - 1])], self.dataset[trial_index, selected_neuron - 1])
            axs[1].set_title(f'Real neuron {selected_neuron} {self.ds_name}. Number of spike(s): {len(np.where(self.dataset[trial_index, selected_neuron - 1] == 1)[0])}')
            axs[1].set_ylabel('Spikes')
            axs[1].set_xlabel('Time (s)')
            axs[1].grid(True)
            axs[1].legend()
            plt.show()

            self.evaluate_similarity(selected_trial=selected_trial, selected_neuron=selected_neuron, art_neuron_output=U_plot, threshold=theta)

        return time, U_plot

    def leaky_if_3(self, selected_trial, selected_neuron, duration=0.2, dt=0.0001, ipsc=np.array([]), arp=.06, verbose=True):
        # PARAMETER SETUP
        # Fixed parameters
        tau = 0.020  # Membrane time constant (seconds)
        R = 3e7      # Membrane resistance (ohms)
        U_rest = -0.07  # Resting potential (volts)
        theta = 3.055  # Threshold for spike initiation (volts)
```

```
    spikeVolt = 10  # Spike value (volts)
    # arp = 0.006  # Absolute refractory period (seconds)
    backgroundI = 3e-9  # Background noise (amps)
    tau_adapt = 0.5  # Decay rate of adaptive threshold
    increase_threshold = 3.255  # Threshold increase after
spike (volts)


    psc = self.input_currents[:]  # Times of excitatory
currents
    U_0 = 0.3
    I_0 = U_0 / R  # Input current (A)
    # ipsc = np.array([])
    # ipsc = np.arange(0, .5, .005)


    # MODEL
    n_pcs = len(psc)
    n_ipcs = len(ipsc)
    index_pscs = np.round(psc / dt).astype(int)
    index_ipscs = np.round(ipsc / dt).astype(int)
    n_steps = int(duration / dt)

    U = np.zeros(n_steps + 1)
    U_plot = np.zeros(n_steps + 1)
    U[0] = U_rest
    U_plot[0] = U_rest

    I = np.zeros(n_steps + 1)
    t_spike = 0
    n_spikes = 0
    time = np.linspace(0, duration, n_steps + 1)
    randI = backgroundI * np.random.normal(0, 1, n_steps)
    theta_adapt = np.full(n_steps + 1, theta)

    # SIMULATION
    for i in range(n_steps):
      for k in range(n_pcs):
        if i == index_pscs[k]:
          I[i] += I_0

      for k in range(n_ipcs):
        if i == index_ipscs[k]:
          I[i] -= I_0

      dU = (dt / tau) * (U_rest - U[i] + I[i] * R + randI[i] *
R)
      U[i + 1] = U[i] + dU
      U_plot[i + 1] = U[i + 1]

      if U[i + 1] > theta_adapt[i]:
        if n_spikes > 0 and time[i] < t_spike + arp:
          U[i + 1] = U[i]
          U_plot[i + 1] = U[i + 1]
        else:
          U_plot[i + 1] = spikeVolt
          U[i + 1] = U_rest
          t_spike = time[i]
          n_spikes += 1
          theta_adapt[i + 1] = theta_adapt[i] +
increase_threshold
      else:
        theta_adapt[i + 1] = theta_adapt[i] + (dt / tau_adapt)
* (theta - theta_adapt[i])

    if verbose:
      n_1, neurons = self.dataset.shape
      times = np.arange(0, (n_1 - 1) * self.bin_size +
self.bin_size, self.bin_size)
      trial_index = (self.trials <= selected_trial)
      # Plotting
      fig, axs = plt.subplots(1, 2, figsize=(15, 6))
      axs[0].plot(time, U_plot, color='black')
      axs[0].axhline(y=theta, color='red', linestyle='--',
label=f'Threshold: {theta * 1000:.1f} mV')
      axs[0].set_title(f'Leaky integrate-and-fire model
{self.ds_name}. Number of spike(s): {n_spikes}')
      axs[0].set_xlabel('Time (s)')
      axs[0].set_ylabel('Voltage (U) (V)')
      axs[0].grid(True)
      axs[0].legend()
      # print(self.dataset[selected_trial, selected_neuron -
1])
      # axs[1].eventplot(np.where(self.spikes == 1)[0] * dt,
color='black')
      axs[1].plot(times[:len(self.dataset[trial_index,
selected_neuron - 1])], self.dataset[trial_index,
selected_neuron - 1])
      axs[1].set_title(f'Real neuron {selected_neuron}
{self.ds_name}. Number of spike(s):
{len(np.where(self.dataset[trial_index, selected_neuron - 1]
== 1)[0])}')
      axs[1].set_ylabel('Spikes')
      axs[1].set_xlabel('Time (s)')
      axs[1].grid(True)
      axs[1].legend()
      plt.show()

      self.evaluate_similarity(selected_trial=selected_trial,
selected_neuron=selected_neuron,
art_neuron_output=U_plot, threshold=theta)

      plt.figure()
      plt.plot(time, theta_adapt, color='red')
      plt.axhline(y=theta, color='red', linestyle='--')
      plt.title(f"Threshold dynamics. Rest threshold: {theta *
1000} mV - ({self.ds_name})")
      plt.xlabel("Time (s)")
      plt.ylabel(f"Threshold (U), number of spikes =
{n_spikes}")
      plt.grid()
      plt.show()

    return time, U_plot
```

```
    def evaluate_similarity(self, selected_trial, selected_neuron, art_neuron_output, threshold):
        trial_index = (self.trials <= selected_trial)
        real_spike_train = self.dataset[trial_index, selected_neuron - 1]

        # Calculate ISI and Spike Count Error
        artificial_spikes = np.where(art_neuron_output >= threshold)[0]
        real_spikes = np.where(real_spike_train == 1)[0]

        real_isi = np.diff(real_spikes) * self.bin_size
        artificial_isi = np.diff(artificial_spikes) * self.bin_size

        spike_count_error = abs(len(real_spikes) - len(artificial_spikes)) / len(real_spikes)

        # Visualization
        plt.figure(figsize=(12, 6))
        plt.hist(real_isi, bins=20, alpha=.5, label='Real ISI')
        plt.hist(artificial_isi, bins=20, alpha=.5, label='Artificial ISI')
        plt.title(f'ISI Comparison for Neuron {selected_neuron} - ({self.ds_name})')
        plt.xlabel('Interspike Interval (s)')
        plt.ylabel('Frequency')
        plt.legend()
        plt.show()

        print("spike_count_error", spike_count_error)
        print("real_isi_mean", np.mean(real_isi))
        print("artificial_isi_mean", np.mean(artificial_isi))

        return {
            "spike_count_error": spike_count_error,
            "real_isi_mean": np.mean(real_isi),
            "artificial_isi_mean": np.mean(artificial_isi)
        }

    def leaky_if_2_test(self, selected_trial, selected_neuron, duration=0.2, dt=0.0001, arp=0.060, verbose=True):
        # Parameters for the Integrate-and-Fire neuron
        V_reset = -65.0  # Reset potential (mV)
        V_th = -0.055    # Threshold potential (mV)
        tau_m = 20.0     # Membrane time constant (ms)
        R_m = 10.0       # Membrane resistance (MΩ)
        I_mean = 1.5     # Mean input current (μA)
        dt = 0.01        # Time step (ms)
        simulation_time = 1000  # Total simulation time (ms)
        n_neurons = 6

        # index_pscs = np.round(psc / dt).astype(int)  # Indices of pulse times
        n_steps = int(duration / dt)  # Number of simulation steps
        U = np.zeros(n_steps + 1)  # Membrane potential array
        U_plot = np.zeros(n_steps + 1)  # Membrane potential for plotting
        # U[0] = U_rest  # Initialize with resting potential
        # U_plot[0] = U_rest
        I = np.zeros(n_steps + 1)  # Input current array
        time = np.linspace(0, duration, n_steps + 1)  # Time array
        n_spikes = 0  # Spike counter
        t_spike = 0 # Addition with respect to LeakyIF_1: Intial time since last spike -will be used in the implementation of the refractory period

        # Simulate a single neuron using Integrate-and-Fire model
        def integrate_and_fire(I_ext):
            V = V_reset
            spikes = []  # Times when spikes occur

            for t in range(len(I_ext)):
                V += (-(V - V_reset) + R_m * I_ext[t]) * dt / tau_m

                if V >= V_th:
                    spikes.append(t * dt)
                    V = V_reset
                else:
                    spikes.append(0)

            return spikes

        spikes = integrate_and_fire(self.input_currents)
        # spike_trains[f"Neuron {neuron + 1}"] = spikes

        if verbose:
            n_1, neurons = self.dataset.shape
            times = np.arange(0, (n_1 - 1) * self.bin_size + self.bin_size, self.bin_size)
            trial_index = (self.trials == selected_trial)
            # Plotting
            fig, axs = plt.subplots(1, 2, figsize=(15, 6))
            # axs[0].plot(time, spikes, color='black')
            axs[0].eventplot(spikes, color='black')
            axs[0].axhline(y=V_th, color='red', linestyle='--', label=f'Threshold: {V_th * 1000:.1f} mV')
            axs[0].set_title(f'Leaky integrate-and-fire model {self.ds_name}. Number of spike(s): {n_spikes}')
            axs[0].set_xlabel('Time (s)')
            axs[0].set_ylabel('Voltage (U) (V)')
            axs[0].grid(True)
            axs[0].legend()
            # print(self.dataset[selected_trial, selected_neuron - 1])
            # axs[1].eventplot(np.where(self.spikes == 1)[0] * dt, color='black')
            axs[1].plot(times[:len(self.dataset[:, selected_neuron - 1])], self.dataset[:, selected_neuron - 1])
```

```
        axs[1].set_title(f'Real neuron {selected_neuron}
{self.ds_name}. Number of spike(s):
{len(np.where(self.dataset[:, selected_neuron - 1] == 1)[0])}')
        axs[1].set_ylabel('Spikes')
        axs[1].set_xlabel('Time (s)')
        axs[1].grid(True)
        axs[1].legend()
        plt.show()

        self.evaluate_similarity(selected_trial=selected_trial,
selected_neuron=selected_neuron,
art_neuron_output=U_plot, threshold=V_th)

    return time, spikes

# %%
# Store Artificial neurons
art_neurons_EME = [
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
]
art_neurons_ORA = [
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
  np.zeros(10),
]

# %% [markdown]
# ### Generating artificial neurons (EME)

# %%
time = len(Spikes_EME[trial_index, 0]) * .01
EXT_INPUT_EME = np.arange(0, 6.5, .0009994)

LIF_EME_neurons1 =
Neuron_Network_test(input_currents=EXT_INPUT_EME,
spikes=Spikes_EME[trial_index, 0], trials=Trials_EME,
ds_name="EME", dataset=Spikes_EME)
artificial_neuron1_EME =
LIF_EME_neurons1.leaky_if_1(selected_trial=selected_trial
s, selected_neuron=1, duration=time, dt=.01)
art_neurons_EME[0] = artificial_neuron1_EME[1][:-1]
# art_neurons_EME.append(artificial_neuron1_EME[1][:-
1])

# %%
time = len(Spikes_EME[trial_index, 1]) * .01
EXT_INPUT_EME = np.concatenate((
  np.arange(0, 1, .000996),
  np.arange(3, 5, .0009989),
  np.arange(12, 13, .00099895)
  ))
LIF_EME_neurons2 =
Neuron_Network_test(input_currents=EXT_INPUT_EME,
spikes=Spikes_EME[trial_index, 1], trials=Trials_EME,
ds_name="EME", dataset=Spikes_EME)
artificial_neuron2_EME =
LIF_EME_neurons2.leaky_if_2(selected_trial=selected_trial
s, selected_neuron=2, duration=time, dt=.01)
art_neurons_EME[1] = artificial_neuron2_EME[1][:-1]
# art_neurons_EME.append(artificial_neuron2_EME[1][:-
1])

# %%
time = len(Spikes_EME[trial_index, 2]) * .01
EXT_INPUT_EME = np.concat((
  np.arange(0, 3, .000998),
  np.arange(7, 13, .0009992),
  ))
LIF_EME_neurons3 =
Neuron_Network_test(input_currents=EXT_INPUT_EME,
spikes=Spikes_EME[trial_index, 2], trials=Trials_EME,
ds_name="EME", dataset=Spikes_EME)
artificial_neuron3_EME =
LIF_EME_neurons3.leaky_if_2(selected_trial=4,
selected_neuron=3, duration=time, dt=.01)
art_neurons_EME[2] = artificial_neuron3_EME[1][:-1]
# art_neurons_EME.append(artificial_neuron3_EME[1][:-
1])

# %%
time = len(Spikes_EME[trial_index, 3]) * .01
EXT_INPUT_EME = np.arange(0, 5, .000998)
LIF_EME_neurons4 =
Neuron_Network_test(input_currents=EXT_INPUT_EME,
spikes=Spikes_EME[trial_index, 3], trials=Trials_EME,
ds_name="EME", dataset=Spikes_EME)
artificial_neuron4_EME =
LIF_EME_neurons4.leaky_if_2(selected_trial=4,
selected_neuron=4, duration=time, dt=.01)
art_neurons_EME[3] = artificial_neuron4_EME[1][:-1]
# art_neurons_EME.append(artificial_neuron4_EME[1][:-
1])

# %%
time = len(Spikes_EME[trial_index, 4]) * .01
EXT_INPUT_EME = np.arange(0, 13, .0009984)
LIF_EME_neurons5 =
Neuron_Network_test(input_currents=EXT_INPUT_EME,
spikes=Spikes_EME[trial_index, 4], trials=Trials_EME,
ds_name="EME", dataset=Spikes_EME)
artificial_neuron5_EME =
LIF_EME_neurons5.leaky_if_2(selected_trial=4,
selected_neuron=5, duration=time, dt=.01)
art_neurons_EME[4] = artificial_neuron5_EME[1][:-1]
# art_neurons_EME.append(artificial_neuron5_EME[1][:-
1])
```

```
# %%
time = len(Spikes_EME[trial_index, 5]) * .01
EXT_INPUT_EME = np.concat((
    np.arange(0, 7.5, .0009984),
    np.arange(11, time, .0009987),
    ))
LIF_EME_neurons6 =
Neuron_Network_test(input_currents=EXT_INPUT_EME,
spikes=Spikes_EME[trial_index, 5], trials=Trials_EME,
ds_name="EME", dataset=Spikes_EME)
artificial_neuron6_EME =
LIF_EME_neurons6.leaky_if_2(selected_trial=4,
selected_neuron=6, duration=time, dt=.01)
art_neurons_EME[5] = artificial_neuron6_EME[1][:-1]
# art_neurons_EME.append(artificial_neuron6_EME[1][:-
1])

# %% [markdown]
# ### Generating ORA

# %%
time = len(Spikes_ORA[trial_index_ORA, 0]) * .01
EXT_INPUT_ORA = np.concat((
    np.arange(0, 1, .000998),
    np.arange(3.5, time, .0009985),
    ))

LIF_ORA_neurons1 =
Neuron_Network_test(input_currents=EXT_INPUT_ORA,
spikes=Spikes_ORA[trial_index_ORA, 0],
trials=Trials_ORA, ds_name="ORA",
dataset=Spikes_ORA)
artificial_neuron1_ORA =
LIF_ORA_neurons1.leaky_if_1(selected_trial=selected_trial
s, selected_neuron=1, duration=time, dt=.01)
art_neurons_ORA[0] = artificial_neuron1_ORA[1][:-1]

# %%
time = len(Spikes_ORA[trial_index_ORA, 1]) * .01
EXT_INPUT_ORA = np.concat((
    np.arange(0, 1, .000996),
    np.arange(3.2, time, .0009992),
    ))

LIF_ORA_neurons2 =
Neuron_Network_test(input_currents=EXT_INPUT_ORA,
spikes=Spikes_ORA[trial_index_ORA, 1],
trials=Trials_ORA, ds_name="ORA",
dataset=Spikes_ORA)
artificial_neuron2_ORA =
LIF_ORA_neurons2.leaky_if_1(selected_trial=selected_trial
s, selected_neuron=2, duration=time, dt=.01)
art_neurons_ORA[1] = artificial_neuron2_ORA[1][:-1]

# %%
time = len(Spikes_ORA[trial_index_ORA, 2]) * .01
EXT_INPUT_ORA = np.concat((
    np.arange(0, 1, .0009985),
    np.arange(2.2, time, .000999),
    ))

LIF_ORA_neurons3 =
Neuron_Network_test(input_currents=EXT_INPUT_ORA,
spikes=Spikes_ORA[trial_index_ORA, 2],
trials=Trials_ORA, ds_name="ORA",
dataset=Spikes_ORA)
artificial_neuron3_ORA =
LIF_ORA_neurons3.leaky_if_2(selected_trial=selected_trial
s, selected_neuron=3, duration=time, dt=.01)
art_neurons_ORA[2] = artificial_neuron3_ORA[1][:-1]

# %%
time = len(Spikes_ORA[trial_index_ORA, 3]) * .01
EXT_INPUT_ORA = np.concat((
    np.arange(0, 1.7, .0009972),
    np.arange(1.9, time, .0009988),
    ))

LIF_ORA_neurons4 =
Neuron_Network_test(input_currents=EXT_INPUT_ORA,
spikes=Spikes_ORA[trial_index_ORA, 3],
trials=Trials_ORA, ds_name="ORA",
dataset=Spikes_ORA)
artificial_neuron4_ORA =
LIF_ORA_neurons4.leaky_if_2(selected_trial=selected_trial
s, selected_neuron=4, duration=time, dt=.01)
art_neurons_ORA[3] = artificial_neuron4_ORA[1][:-1]

# %%
time = len(Spikes_ORA[trial_index_ORA, 4]) * .01
EXT_INPUT_ORA = np.concat((
    np.arange(0, 1.7, .0009979),
    np.arange(1.9, time, .000996),
    ))

LIF_ORA_neurons5 =
Neuron_Network_test(input_currents=EXT_INPUT_ORA,
spikes=Spikes_ORA[trial_index_ORA, 4],
trials=Trials_ORA, ds_name="ORA",
dataset=Spikes_ORA)
artificial_neuron5_ORA =
LIF_ORA_neurons5.leaky_if_2(selected_trial=selected_trial
s, selected_neuron=5, duration=time, dt=.01)
art_neurons_ORA[4] = artificial_neuron5_ORA[1][:-1]

# %%
time = len(Spikes_ORA[trial_index_ORA, 5]) * .01
EXT_INPUT_ORA = np.arange(0, 4.2, .000998)

LIF_ORA_neurons6 =
Neuron_Network_test(input_currents=EXT_INPUT_ORA,
spikes=Spikes_ORA[trial_index_ORA, 5],
```

```
trials=Trials_ORA, ds_name="ORA",
dataset=Spikes_ORA)
artificial_neuron6_ORA =
LIF_ORA_neurons6.leaky_if_2(selected_trial=selected_trials, selected_neuron=6, duration=time, dt=.01)
art_neurons_ORA[5] = artificial_neuron6_ORA[1][:-1]

# %% [markdown]
# ## Optimal window size for Artificial neurons

# %%
art_neurons_EME = np.array(art_neurons_EME.copy())
art_neurons_ORA = np.array(art_neurons_ORA.copy())

art_neurons_EME[art_neurons_EME == 10] = 1 # Replace by value 1 all values that are equal to 10 (10 means a spike occurred)
art_neurons_EME[art_neurons_EME != 1] = 0 # Replace by value 0 all values that are not equal to 10 (10 means a spike occurred)

art_neurons_ORA[art_neurons_ORA == 10] = 1 # Replace by value 1 all values that are equal to 10 (10 means a spike occurred)
art_neurons_ORA[art_neurons_ORA != 1] = 0 # Replace by value 0 all values that are not equal to 10 (10 means a spike occurred)

# %%
Optimal_win_size_Generated_EME =
Find_optimal_window(ds=art_neurons_EME.T,
ds_trials=Trials_EME[trial_index],window_start=.01,
window_stop=1, ds_name="EME (Artificial)")
Optimal_win_size_Generated_ORA =
Find_optimal_window(ds=art_neurons_ORA.T,
ds_trials=Trials_ORA[trial_index_ORA],window_start=.01,
window_stop=1, ds_name="ORA (Artificial)")

# %%
Optimal_win_size_Generated_EME.sliding_window_trial(trial_num=4)

# %%
Optimal_win_size_Generated_ORA.sliding_window_trial(trial_num=4)

# %% [markdown]
# - 0.3 Seems like the ideal window size for EME
# - 0.18 Seems like the ideal window size for ORA

# %% [markdown]
# ## Display rate and correlations (artificial spikes)

# %%
Firing_Rate_Generated_EME =
Fire_Rate_Estimation(spikes=art_neurons_EME.T,
trials=Trials_EME[trial_index], dataset_name="EME
(Artificial)")
Firing_Rate_Generated_ORA =
Fire_Rate_Estimation(spikes=art_neurons_ORA.T,
trials=Trials_ORA[trial_index_ORA], dataset_name="ORA
(Artificial)")

# %%
rate_generated_EME =
Firing_Rate_Generated_EME.Calculate_rate(window_size=.3)
rate_generated_ORA =
Firing_Rate_Generated_ORA.Calculate_rate(window_size=.18)

# %%
Firing_Rate_Generated_EME.display_aggregated_plot(rate_generated_EME)
Firing_Rate_Generated_ORA.display_aggregated_plot(rate_generated_ORA)

# %%
Firing_Rate_Generated_EME.Calculate_corrolation_coef(rate_generated_EME)

# %%
Firing_Rate_Generated_ORA.Calculate_corrolation_coef(rate_generated_ORA)

# %% [markdown]
# ## Model classification

# %%
from sklearn.model_selection import train_test_split, KFold,
LeaveOneOut
from sklearn.metrics import accuracy_score, log_loss
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import
LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

@dataclass
class Classification_model():
    neurons_data: 'NDArray'
    dataset_name: str
    ground_truth: 'NDArray'
    dataset_type: str
```

```
    def build_model_fold(self, data_distribution: float,
selected_model, fold_num: int):

        X, y = self.neurons_data, self.ground_truth
        X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=data_distribution, random_state=42)

        k = fold_num  # Number of folds
        kf = KFold(n_splits=k, shuffle=True,
random_state=42)  # Create KFold object

        accuracy_scores = []
        model_pred = []
        model_test = []

        for train_index, val_index in kf.split(X):
            X_train, X_val = X[train_index], X[val_index]
            y_train, y_val = y[train_index], y[val_index]

            model = selected_model()  # Initialize the model
            model.fit(X_train, y_train) # Train the model

            y_pred = model.predict(X_val)  # Make predictions

            [model_pred.append(pred) for pred in y_pred]
            [model_test.append(test_val) for test_val in y_val]

        print("Selected model: ", selected_model().__str__(), f"-
Dataset name: {self.dataset_name} -", self.dataset_type)
        self._model_evaluation_metrics(y_test=model_test,
predictions=model_pred)

    def build_model_leave_one_out(self, data_distribution:
float, selected_model):
        X, y = self.neurons_data, self.ground_truth
        X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=data_distribution, random_state=42)

        loo = LeaveOneOut()
        results = []
        model_pred = []
        model_test = []

        for train_index, test_index in loo.split(X):
            X_train, X_test = X[train_index], X[test_index]
            y_train, y_test = y[train_index], y[test_index]

            knn = selected_model()
            knn.fit(X_train, y_train)
            prediction = knn.predict(X_test)

            [model_pred.append(pred) for pred in prediction]
            [model_test.append(test_val) for test_val in y_test]


        print("Selected model: ", selected_model().__str__(), f"-
Dataset name: {self.dataset_name} -", self.dataset_type)
```

```
        self._model_evaluation_metrics(y_test=model_test,
predictions=model_pred)

    def compare_models(self, data_distribution: float):
        X, y = self.neurons_data, self.ground_truth
        X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=data_distribution, random_state=42)

        # ML algorithms
        models = []
        models.append(('Linear Regression',
LogisticRegression(solver = 'liblinear', multi_class= 'ovr')))
        models.append(("Linear Discriminant Analysis",
LinearDiscriminantAnalysis()))
        models.append(("Decision Tree Classifier",
DecisionTreeClassifier()))
        models.append(("K-Neighbors Classifier",
KNeighborsClassifier()))
        models.append(("Gaussian NB", GaussianNB()))
        models.append(("SVM", SVC()))

        results = []
        names = []
        for name, model in models:
            cv = KFold(n_splits=20, random_state=None)
            scores = cross_val_score(model, X_train, y_train,
scoring="accuracy", cv=cv)
            names.append(name)
            results.append(scores)
            print("%s - Model accuracy: %.2f - Model error rate:
(%.2f)" % (name, scores.mean(), scores.std()))

        # compare algorithm
        fig = plt.figure(figsize=(15, 8))
        fig.suptitle(f"Algorithm Comparison {self.dataset_name}
- {self.dataset_type}")
        ax = fig.add_subplot(111)
        plt.boxplot(results)
        ax.set_xticklabels(names)
        ax.set_ylabel("Accuracy score")
        plt.show()

    def _model_evaluation_metrics(self, y_test, predictions):
        conf_matrix = confusion_matrix(y_test, predictions)
        self._show_confusion_matric(conf_matrix)
        #Evaluate Prediction
        print('Accuracy Score:', accuracy_score(y_test,
predictions), "\n")

        # print('Confusion Matrix')
        # print(confusion_matrix(y_test, predictions), "\n")

        print('Classification Report')
        print(classification_report(y_test, predictions,
zero_division=1))

    def _show_confusion_matric(self, cnn_matrix):
```

```
        labels = np.unique(self.ground_truth)
        plt.figure(figsize=(6,5))
        sns.heatmap(cnn_matrix, annot=True, fmt='d',
cmap='Reds', xticklabels=labels, yticklabels=labels)
        plt.xlabel('Predicted label')
        plt.ylabel('True Label')
        plt.title(f'Confusion Matrix {self.dataset_name} -
({self.dataset_type})')
        plt.show()

# %%
selected_trials = 4
trial_index_EME = (Trials_EME <= selected_trials) # First 4
trials
trial_index_ORA = (Trials_ORA <= selected_trials) # First 4
trials

# %%
print("Ground truth classes number for first 4 trials (EME)")
for i in np.unique(ground_tr_EME[trial_index_EME]):
    print("Class", int(i))

print("Ground truth classes number for first 4 trials (ORA)")
for i in np.unique(ground_tr_ORA[trial_index_ORA]):
    print("Class", int(i))

# %% [markdown]
# ### Model classification of real neurons

# %%
CLASSIFICATION_EME =
Classification_model(neurons_data=rate_EME[trial_index_
EME, :-1], dataset_name="EME",
ground_truth=ground_tr_EME[trial_index_EME],
dataset_type="Real neurons")
CLASSIFICATION_ORA =
Classification_model(neurons_data=rate_ORA[trial_index_
ORA, :-1], dataset_name="ORA",
ground_truth=ground_tr_ORA[trial_index_ORA],
dataset_type="Real neurons")

# %%
CLASSIFICATION_EME.compare_models(data_distributio
n=.2)

# %%
CLASSIFICATION_ORA.compare_models(data_distributio
n=.2)

# %% [markdown]
# - Decision Tree looks like the best performing model

# %%
CLASSIFICATION_EME.build_model_fold(data_distributi
on=.2, selected_model=DecisionTreeClassifier,
fold_num=15)

# %%
CLASSIFICATION_ORA.build_model_fold(data_distributi
on=.2, selected_model=DecisionTreeClassifier,
fold_num=15)

# %% [markdown]
# ### Model classification for artificial neurons

# %%
CLASSIFICATION_Generated_EME =
Classification_model(neurons_data=art_neurons_EME.T,
dataset_name="EME",
ground_truth=ground_tr_EME[trial_index_EME],
dataset_type="Artificial neurons")
CLASSIFICATION_Generated_ORA =
Classification_model(neurons_data=art_neurons_ORA.T,
dataset_name="ORA",
ground_truth=ground_tr_ORA[trial_index_ORA],
dataset_type="Artificial neurons")

# %%
CLASSIFICATION_Generated_EME.compare_models(data
_distribution=.2)

# %%
CLASSIFICATION_Generated_ORA.compare_models(data
_distribution=.2)

# %%
CLASSIFICATION_Generated_EME.build_model_fold(data
_distribution=.2, selected_model=DecisionTreeClassifier,
fold_num=15)

# %%
CLASSIFICATION_Generated_ORA.build_model_fold(data
_distribution=.2, selected_model=GaussianNB,
fold_num=15)
```