

Introduction

Several mathematical models of spiking behavior are used to build Spiking Neural Networks (SNNs) models [1]. SNNs have potential applications in various fields, however, implementing SNNs can be challenging, especially when it comes to classification tasks that require high accuracy and low-performance loss. To address this issue, our study compares,

- The performance of different SNN models and analysis of the results to determine the most effective one.
- And emphasizes the importance of comparing different models to determine the most suitable one.

Types of SNN Models

This study involved simulating three different neuron models:

- The leaky integrate-and-fire (LIF) model [2]
- The nonlinear LIF (NLIF) model [3]
- The adaptive exponential (AdEx) model [4]

Each model is characterized by a system of differential equations that govern the dynamics of the neuron's voltage and other state variables as they respond to input currents.

Synthetic Dataset

The synthetic dataset consists of 1000 samples with two features, $x_1 \sim N(0, 1)$ and $x_2 \sim N(3, 1)$, and a binary target vector, y , of length $2n$ where the first n elements are 0 and the last n elements are 1. The dataset is shuffled using a random permutation of indices $indices = [0, 1, \dots, 2n - 1]$, and X and y are updated accordingly.

Evaluating SNN Models

We evaluated the model's performance by calculating classification accuracy and performance loss, and by visualizing the spiking activity of randomly initialized neurons. The models were run with 1000 inputs and neurons, with varying parameters.

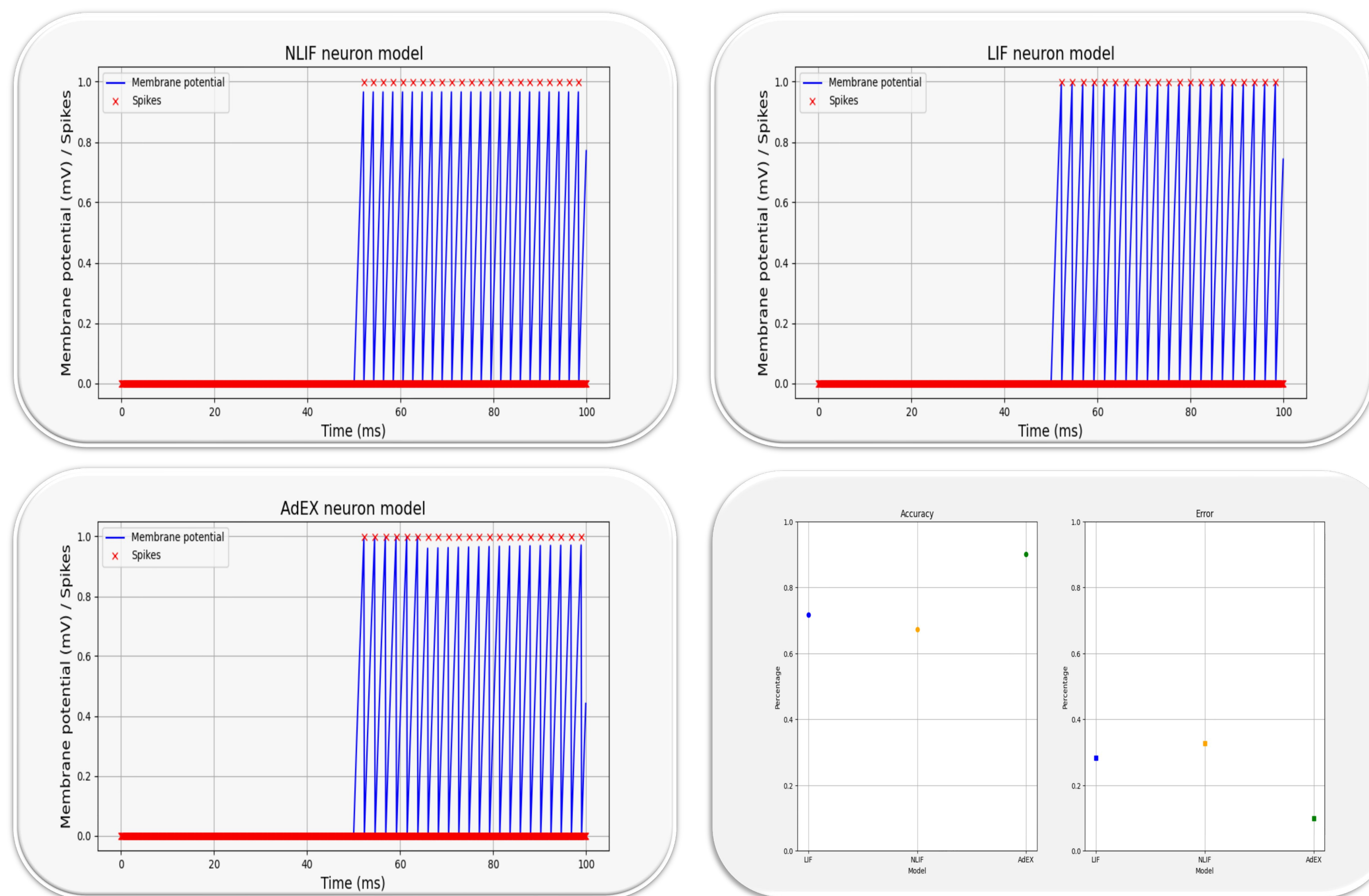
	LIF	NLIF	AdEX
Classification Accuracy	71.65%	67.05%	90.65%

Table 1: Performance Comparison: Classification Accuracy

	LIF vs NLIF	NLIF vs AdEX	AdEX vs LIF
Performance Loss	-6.86%	-35.20%	-26.52%

Table 2: Performance Comparison: Performance Loss

Spiking Activity of each SNN Model



Performance

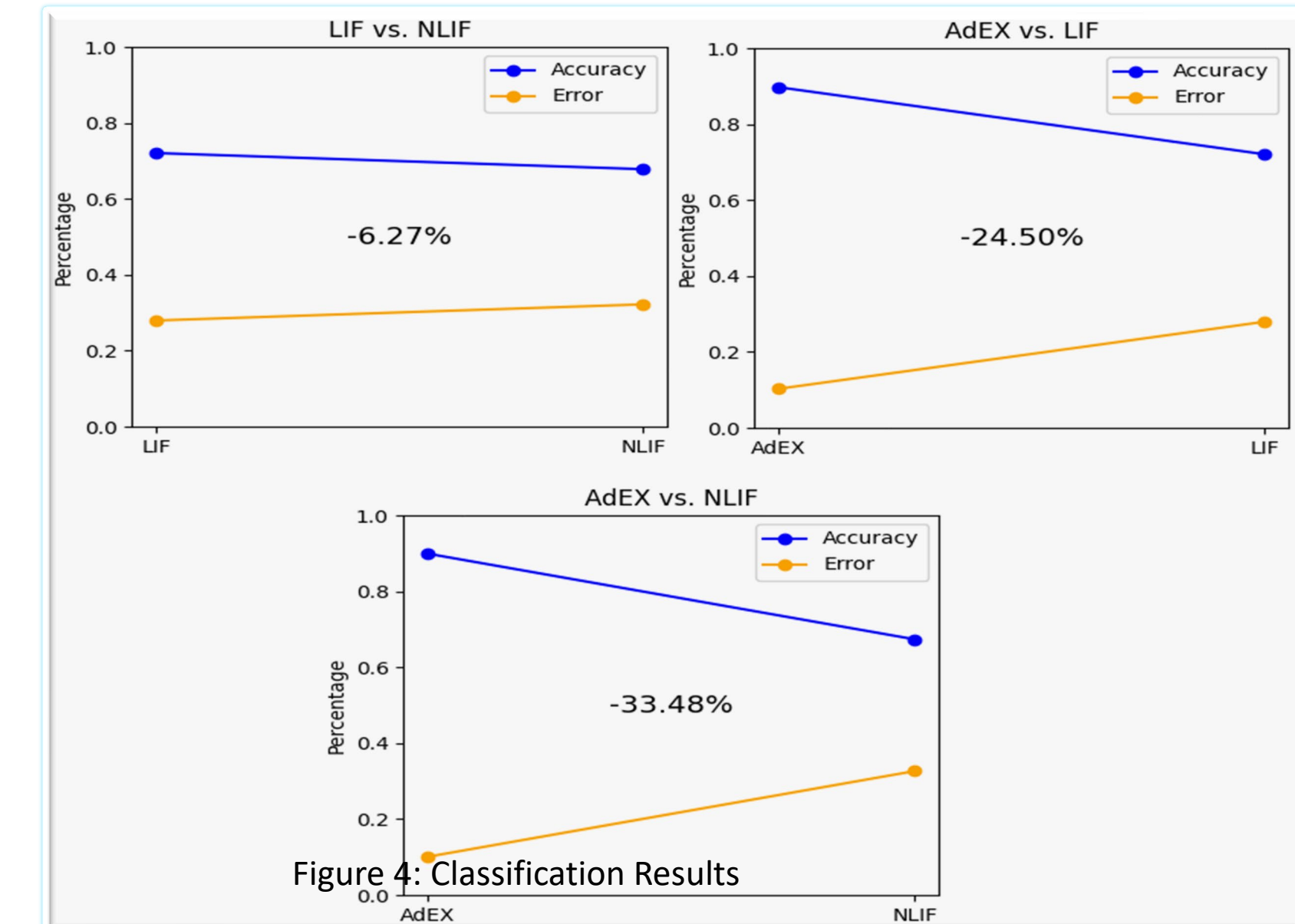


Figure 4: Classification Results

Conclusion

A study compared different SNN models using the same inputs and neurons, evaluating their performance and providing insights for researchers and practitioners. Further research could explore additional models and benchmarks to determine the most suitable model for specific applications, potentially saving time and resources. Overall, the study highlights the potential benefits of SNNs and offers valuable insights for future research and development.

Conclusion

- [1] Samanwoy Ghosh-Dastidar and Hojjat Adeli. Spiking neural networks. 2009.
- [2] Doron Tal and Eric L Schwartz. Computing with the leaky integrate-and-fire neuron: logarithmic computation and multiplication. 1997.
- [3] Renaud Jolivet, Timothy J Lewis, and Wulfram Gerstner. Generalized integrate-and-fire models of neuronal activity approximate spike trains of a detailed model to a high degree of accuracy. 2004.
- [4] Wulfram Gerstner and Romain Brette. Adaptive exponential integrate-and-fire model. Scholarpedia, 2009.