Learning Permutation Matrix Patterns in the NARMA Dataset with Spiking Neural Networks: A Spike-Timing-Dependent-Plasticity Based Approach

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***Abstract*—Spiking Neural Networks (SNNs) provide a biologically inspired framework for temporal pattern recognition, with the potential to address complex, real-world data. Building on established training methods based on spike-timing dependent plasticity (STDP), this work investigates the applicability of SNNs to the classification of structured patterns within the Non-linear AutoRegressive Moving Average (NARMA) time series dataset. By representing segments of market data as permutation matrices and leveraging STDP-driven adaptation, we evaluate the network's ability to distinguish diverse temporal patterns. Experimental results on the NARMA dataset, derived from historical SP 500 data, demonstrate that the SNN can capture certain structured trends; however, overall classification accuracy is constrained by the limited dataset size (approximately 500 matrices) and the complexity of overlapping classes. These findings highlight both the promise and current challenges of applying neuromorphic models to time series analysis, and suggest directions for advancing bio-inspired computation in practical domains.**

***Index Terms*—Pattern recognition, Spiking Neural Networks, Computational models, Neuromorphic computing, Non-linear AutoRegressive Moving Average, Time series analysis**

I. Introduction

In today's world, software-driven intelligent systems are increasingly pervasive, embedded in everything from consumer electronics to critical infrastructure. As the boundaries between digital and biological systems blur, there is growing interest in computational models that more closely mimic biological intelligence. Spiking Neural Networks (SNNs), often described as the third generation of neural networks, are inspired by the event-driven communication and plasticity observed in real neural circuits. Unlike traditional artificial neural networks, SNNs process information through discrete spikes and adapt their connections using biologically plausible learning rules such as spike-timing dependent plasticity (STDP). This enables them to efficiently capture complex temporal and spatial patterns [1] [2], making them promising for tasks where timing and sequence matter.

Financial time series, such as stock market indices, are a prime example of real-world data characterized by non-stationarity, noise, and intricate temporal dependencies. While deep learning models like LSTMs have achieved success in forecasting [3], they often lack biological plausibility and can be computationally intensive. SNNs, with their event-driven processing and energy efficiency, offer an attractive alternative for modeling and classifying such data [4]. However, their effectiveness in this domain remains underexplored.

In this work, we select the S&P 500 index as a representative example of financial time series data. Instead of relying on raw numerical values, we preprocess the data into permutation matrices that capture the relative ordering of values within short time windows. This structured approach allows the SNN to efficiently and interpretably recognize temporal patterns. Our model architecture, learning methodology, and evaluation procedures are adapted from established SNN research, ensuring both comparability with prior studies and reproducibility of results.

The rest of this report is organized as follows. Section 2 reviews related work in SNN-based pattern recognition. Section 3 details the computational model and data preprocessing pipeline. Section 4 presents experimental results and analysis. Section 5 concludes with a discussion of findings and future directions.

II. Related Work

Spiking Neural Networks (SNNs) represent the third generation of neural network models, distinguished by their biological plausibility and ability to process information through discrete spike events. Foundational research by Maass and others established the computational advantages of SNNs for tasks involving temporal and spatial pattern recognition, inspiring their adoption in domains where timing and event-driven computation are essential.

Recent advances have demonstrated SNNs' effectiveness in a variety of pattern recognition applications, such as speech processing, robotics, and neuromorphic vision. The development of learning rules like spike-timing dependent plasticity (STDP) and surrogate gradient methods has enabled SNNs to achieve competitive performance with traditional artificial neural networks, while also offering benefits in energy efficiency and temporal modeling. Modern software frameworks have further accelerated the deployment of SNNs on both simulated and neuromorphic hardware.

Despite these advances, the use of SNNs for structured time series analysis in financial domains remains underexplored, with most prior work focused on synthetic or benchmark datasets. Building on the biologically inspired training approach of the seed paper [5], our study applies SNNs to the classification of permutation matrix patterns derived from real-world financial data, aiming to assess both the capabilities and limitations of SNNs in this challenging context.

III. Methodology

This section describes the computational model used in this study, which is adapted from established spiking neural network (SNN) frameworks for pattern recognition. The model consists of simple spiking neurons, fixed synaptic weights initialized to canonical patterns, and a feedforward network architecture designed to classify structured permutation matrices derived from financial time series data.

A. Spiking Neuron Model

Each neuron in the network is implemented as a leaky integrate-and-fire (LIF) unit, which is computationally efficient and sufficient for capturing the essential dynamics required for spike-based pattern recognition.

The membrane potential of each neuron is incremented by weighted input spikes and decays over time, with a threshold mechanism triggering a spike and subsequent reset. The neuron enters a brief refractory period after spiking, during which it does not respond to inputs. This model balances biological plausibility with computational simplicity, making it well-suited for large-scale simulations and real-time applications.

B. Synaptic Model and Weight Initialization

Synaptic connections between input and output neurons are represented by fixed weights, initialized to reflect canonical patterns corresponding to distinct classes in the dataset. Unlike some SNN studies that employ online learning via spike-timing-dependent plasticity (STDP), this work uses static weights to focus on the network's ability to classify patterns based on pre-defined templates. The weight matrices are constructed so that each output neuron is maximally responsive to a specific permutation pattern, facilitating direct evaluation of the network's classification capabilities.

C. Network Architecture

The network consists of a single-layer feedforward SNN with 25 input neurons (one for each element of the 5×5 permutation matrix) fully connected to 5 output neurons, each representing a pattern class. Input matrices are encoded as spike trains and presented over 20 discrete time steps. At each step, output neurons integrate weighted spikes, and lateral inhibition ensures only the most active neuron can spike. The final class prediction is made by selecting the neuron with the highest total spike count.

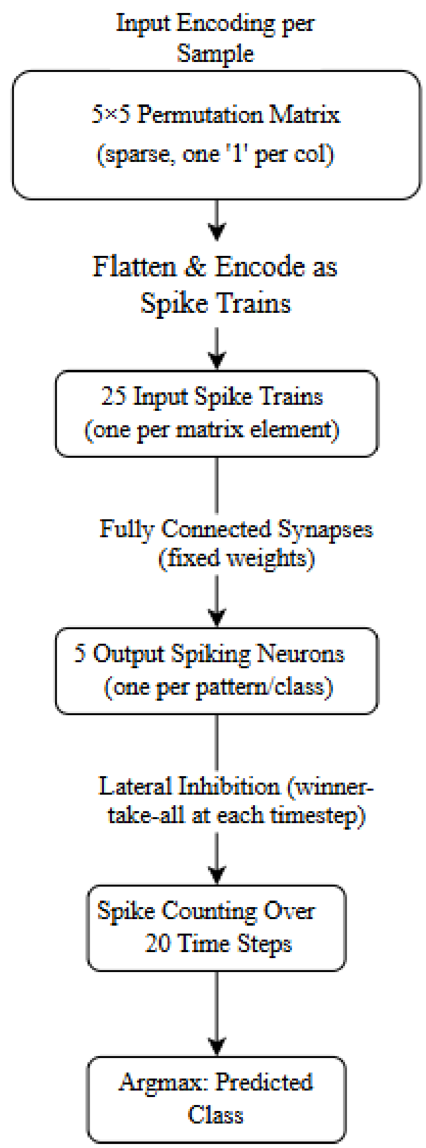


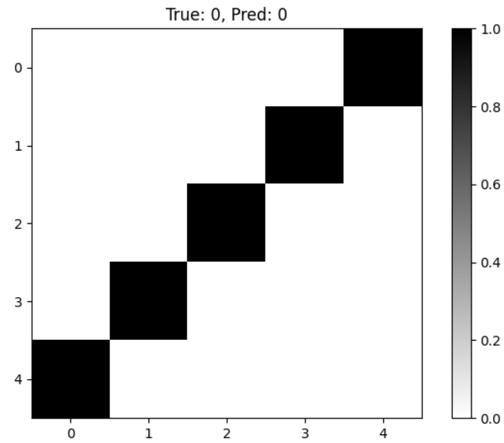
Fig. 1. Network Architecture

IV. Training Method and Evaluation

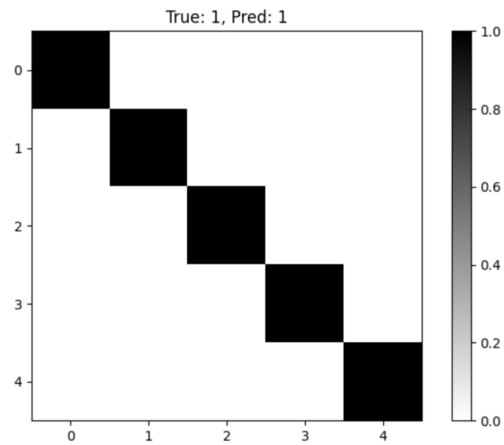
This section outlines the classification workflow, input encoding, and evaluation protocol for assessing SNN performance on the NARMA dataset. The process involves presenting each encoded permutation matrix to the network, recording output neuron activity, and comparing predictions to true labels to quantify accuracy and error types.

A. Pattern Recognition Task

Each classification sample consists of a 5×5 permutation matrix generated from a segment of five consecutive S&P 500 index values. For each segment, the relative ranking of the values is encoded such that each column contains a single '1' at the row corresponding to that day's rank, resulting in a sparse binary matrix. The SNN is tasked with assigning each matrix to one of five predefined pattern classes as shown below.



Class 0



Class 1

Fig. 2. Classes based on the patterns.

B. Input Encoding and Test Protocol

Each input matrix is converted to a float array and encoded into a stochastic spike train for each input neuron, simulating event-driven SNN input. The network processes these spike trains over 20 time steps. Output neurons integrate spikes, and lateral inhibition suppresses all but the most active neuron. Weights are fixed and initialized to canonical patterns; no learning occurs during testing. The neuron with the most spikes across the window is the predicted class.

C. Evaluation Metrics

Performance is evaluated using several metrics:

- Success rate: Proportion of correctly classified samples.
- False positives: Proportion of incorrect predictions.
- Always-firing: Cases where multiple neurons spike equally.
- No learning: Cases where no neuron spikes.
- Inverse learning: Cases where class 4 is confused with others, or vice versa.

A confusion matrix summarizes prediction outcomes across all classes, providing a visual assessment of classification performance.

TABLE I
EVALUATION METRICS

Metric	Value
Success rate	0.381
Always-firing	0.151
False positives	0.467
No learning	0.000
Inverse learning	0.259

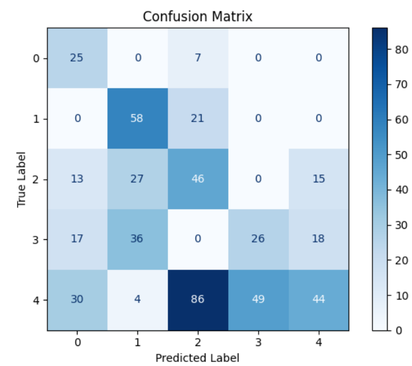


Fig. 3. Confusion Matrix

V. DISCUSSION

Building on established Spiking Neural Network (SNN) architectures, this study adapts their biologically inspired framework to classify structured financial time series encoded as permutation matrices. Using the NARMA dataset-comprising 522 matrices derived from historical S&P 500 segments-we evaluated the SNN's ability to discern temporal patterns. The network achieved 38.1% accuracy, successfully identifying canonical trends (e.g., strictly increasing/decreasing sequences) as shown in table 1, but struggling with overlapping or complex classes, such as mixed or V-shaped patterns. These limitations stem from both the dataset's restricted size and the fixed synaptic weights, which lack adaptability to nuanced variations.

To address these challenges, future work will integrate Spike-Timing-Dependent Plasticity (STDP) to enable dynamic weight adjustments during training, enhancing discrimination of ambiguous patterns. Hybrid architectures combining SNNs with traditional models (e.g., LSTMs) could leverage complementary strengths, while expanding the dataset to diverse financial indices (e.g., NASDAQ, DJIA) would test scalability. Such advancements promise to bridge neuromorphic computing with practical financial analytics, offering energy-efficient solutions for real-world trend analysis.

VI. CONCLUSION

This work explored the application of Spiking Neural Networks (SNNs) to the classification of structured financial time series, using permutation matrices derived from segments of the S&P 500 index as input. By leveraging a biologically inspired, event-driven neural architecture with fixed synaptic weights, we evaluated the ability of SNNs to recognize temporal patterns within the NARMA dataset. The network demonstrated selective success in identifying canonical trends, but overall accuracy was limited to 38.1%, with significant confusion among complex or overlapping classes.

These findings highlight both the promise and the current limitations of SNNs for real-world pattern recognition in financial data. The use of static weights and a relatively small dataset constrained the model's ability to generalize to more ambiguous or nuanced patterns. Nevertheless, the results affirm the potential of SNNs as interpretable and energy-efficient classifiers for structured temporal data, particularly when pattern classes are well-defined and separable.

Future work will focus on enhancing the adaptability and robustness of SNNs by integrating online learning mechanisms such as spike-timing-dependent plasticity (STDP), exploring hybrid models that combine SNNs with traditional neural architectures [6] [7], and expanding the dataset to include more diverse financial indices. Such advancements are expected to improve classification performance and further establish the role of neuromorphic computing in practical time series analysis and financial engineering.

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