USING SPIKING NEURAL NETWORKS TO ASSIST FINE ART AND PHILOLOGY STUDY: TO CLASSIFY STYLES OF CHINESE CALLIGRAPHY WITH MINIMAL COMPUTING POWER

Zheng Luan[1], Xiangqi Kong[2], Shuimu Zeng[3], Yuke Yao[1], Yaxuan Zhang[4], Xuerui Qiu[1*]
[1]School of Optoelectronic Science and Engineering
University of Electronic Science and Technology of China (UESTC)
{zheng.luan, 2021050905015, sherry.qiu}@std.uestc.edu.cn
[2]School of Automation Engineering, UESTC, 2021060906017@std.uestc.edu.cn
[3]Department of Computer Science, University of Liverpool, sgszeng3@liverpool.ac.uk
[4]School of Computer Science, Nanjing University of Information Science and Technology
202083300496@nuist.cn

ABSTRACT

Spiking Neural Networks have drawn much attention for their potential deployment in low computing power scenarios and interdisciplinary research. This paper focuses on a novel task of classifying Chinese Calligraphy styles properly and introduces a cutting-edge network called CaStySNN. Compared to same-structured traditional artificial neural networks, CaStySNN requires significantly less computing power, while demonstrating superior performances across different datasets. In the future, this innovative approach can be applied to neuromorphic devices, offering solutions to a wide range of challenges in the realms of fine arts and philology.

1 INTRODUCTION AND MOTIVATION

Spiking Neural Networks (SNN) is a brain-inspired artificial neural network (ANN). Since it is low-carbon, parallel-computing-friendly, and requires minimal computing power Fang et al. (2023). It attracts researchers from many areas to study its potential for cross-discipline study and is widely praised as the "third generation" ANN Maass (1997). In the past few years, SNN has achieved very competitive performances in classification tasks Niu et al. (2023). However, some limitations still exist and SNN-based image processing Qiu et al. (2023b) always requires temporal data like video Kim et al. (2020) or special hardware like an event camera Liu et al. (2021); Zhu et al. (2022).

Chinese calligraphy is essential for ancient Chinese intellectuals, surpassing even math and painting. A.3 It can help children learn other skills Winner (1989) and potentially impacts cognitive abilities Lui et al. (2021). However, when AI experts research it, misconceptions arise. Firstly, Chinese calligraphy style (script) [1] is not font Chiang (1973); Li (2010) and to classify font and style together Li et al. (2022) is meaningless. Secondly, relevant classification studies focus on individual characters rather than style Chen (2021). Lastly, the research about alphabetic languages Vijayakumar & Vinothkanna (2020) is often impractical and unsuitable for Chinese (non-alphabetic).

This paper aims to unleash the potential of SNNs in fine art and philology areas. A LeNet-based LeCun et al. (1998) SNN is used to classify different styles of Chinese calligraphy. Chinese calligraphy attracts researchers from multiple areas, but many of them cannot utilize big model AI due to overly complex architecture and enormous computational requirements. Jang et al. (2023) Hence, we adopt a very simple network architecture, coding method, and artificial neuron to leverage the low computing power requirements of SNNs. Despite its simplicity, our approach demonstrates competitive performance. The main contributions can be summarized as follows:

(1) We present, to the best of our knowledge, the first SNN-based and at the same time the first deep-learning-based Chinese calligraphy style classifier. [2]

(2) We demonstrate the multidisciplinary potential of SNNs to help understand fine art and philology. Moreover, the adoption of the "virtual temporal" concept Qiu et al. (2023a) liberates SNNs from temporal data limitations, making them applicable to a wide range of image processing tasks.

*Corresponding Author

[1]Style is widely accepted. Some agencies, such as the Asian Art Museum, prefer to use scripts.

[2]Here, we double-emphasize that style and font are different.

2 METHOD AND EXPERIMENT

Architecture: is a LeNet-based SNN (CaStySNN) where spiking neurons replace activation functions. The first two layers are convolution layers. In each of them, convolution, spiking neuron and pooling will be performed in order. The subsequent layers are two full connection layers with one spiking neuron in each. The final layer serves as the output layer.

Spiking Neuron: For SNN, spiking neurons retain biological interpretability Hodgkin & Huxley (1952). To save computing power, the integrate-and-fire (IF) model is chosen for CaStySNN which is the simplest neuron Burkitt (2006) and is characterized as below Gerstner et al. (2014):

$$\tau \frac{du(t)}{dt} = -u(t) + x(t) \tag{1}$$

where $u(t)$ is the membrane potential at time t, and $x(t)$ is inputs from the presynaptic neurons, and τ is a time constant. To understand the mechanism, the chain rule of IF is expressed more iteratively Wu et al. (2018) in A.2.

Coding Method: Input-output coding is also important for SNN Kim et al. (2022), especially for image processing. CaStySNN chooses direct coding for both input and output to keep simplicity.

Loss and Backpropagation: The loss function is a cross-entropy loss which is shown below.

$$H(p, \hat{p}) = -\sum\nolimits_{i=1}^{N} p(x_i) \log_2(\hat{p}(x_i)) \tag{2}$$

where $\hat{p}$ is the predicted probability. The backpropagation of this work refers to Backpropagation-Through-Time (BPTT) Neftci et al. (2019) and A.2.

Results: Table 1 shows the outstanding performance of CaStySNN. To adopt appropriate T, CaStySNN is more accurate than ANN after 100 epochs for both dataset combinations.

Data Combination \ Net	T=2	T=4	T=6	T=8	ANN
3 common styles	84.28%	85.05%	83.39%	**85.51%**	83.78%
3 + Oracle + e-typography	**81.73%**	77.23%	79.08%	76.71%	80.32%

Table 1: The classification accuracy of CaStySNN and comparable ANN. T is the number of timesteps for CaStySNN. ANN has the same LeNet structure and solely replaces IF with ReLU. The insight of data combinations is in A.1. Ablation study on T is also discussed in A.4.

Analysis and Discussion: The difficulty of this task should not be underestimated. For well-educated university students in China, only 16.67% can recognize and use a style besides Kai (Li et al., 2023). The example images 2 show the similarity and difficulty. The performance of ANN also confirms that this task is challenging for light networks. For the relevant study, ANN is sometimes superior to SNN while sometimes the opposite (Qiu et al., 2023a). In the future A.7, CaStySNN may make full use of motion information to aid related research (Wang et al., 2022).

Computing Power: CaStySNN is a lightweight network and even sacrifices performance to some extent. This is due to the lack of computing sources in philology and fine art areas (Ma & Sun, 2020), and the lack of energy in field archaeology (Wright et al., 2005). CaStySNN (T=2) ideally requires only 1/13000 of the computing power and corresponding energy compared to ANN when implemented on neuromorphic devices. A.6

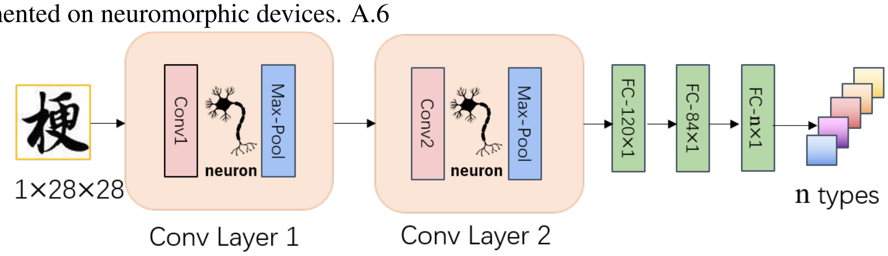

Figure 1: The workflow of CaStySNN.

3 CONCLUSION

In summary, this paper introduces the application of Spiking Neural Networks (SNNs) in Chinese calligraphy style classification, using a LeNet-based SNN (CaStySNN). The simplicity of CaStySNN's architecture, coding method, and spiking neuron effectively tackles the common computing resource limitations faced in philological and fine art studies. Experiment results reveal superiority to same-structure ANN, showcasing the potential of SNN's versatility. The methodology is stated in the main text while necessary knowledge about spiking neurons, Chinese calligraphy, statistical technique and experiment environment are supplemented in the appendix. Additionally, CaStySNN is ideal for neuromorphic devices to greatly save computing power. The promising results even show the broader future of SNN in more interdisciplinary studies.

4 URM Statement

The authors acknowledge that **ALL** authors of this work meet the URM criteria of the ICLR 2024 Tiny Papers Track.

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A Appendix

A.1 Data and Data Availability

The dataset of this work consists of regular style (Kai), running style (Xing), cursive style (Cao), Oracle, and e-typeaces. The 3 common styles are Kai, Xing, and Cao. Each consists of three famous calligraphers' characters equally. SUN Guoting, MAO Zedong, and YU Youren for Cao style; WANG Xizhi, ZHU Da, and MI Fu for Xing style; HAN Yu, LIU Gongquan and YAN Zhenqing for Kai style. This combination removes controversial modern artists in Wang (2021) and Li et al. (2022) which is the source of this work. The Oracle is from oracle bones and Pre-Qin-Dynasty bronzes (Jin Wen and Da Zhuan). The e-typography style here is Caiyun art words. To show the CaStySNN is an effective slight network, each dataset only contains 579 characters. All the images are preprocessed to 28$\times$28 gray image.
Examples of our data are shown below. The difference between each style is relatively small.

Figure 2: There are three characters randomly picked from our three common style dataset combinations. Graph (a) is a Chinese character ”han” from SUN Guoting's Cao style. (b) and (c) is ”geng” and ”shang” from WANG Xizhi's Xing style and YAN Zhenqing's Kai style, correspondingly. Additionally, (d) is ”duo” from Oracle style and (e) is ”guo” from e-typography.

A.2 Chain Rule of IF

We use the iterative IF Wu et al. (2018) to build our SNN architecture. It can be concluded as follows:

$$U^i_{t+1,n} = U^i_{t,n} \cdot (1 - S^i_{t,n}) + X^i_{t+1,n}, \tag{3}$$

$$S^i_{t+1,n} = \Theta(U^i_{t+1,n} - V_{th}), \tag{4}$$

where $U(t)$ and $S(t)$ represents the membrane potential and the spike output, $X(t)$ represents the input from the presynaptic neurons. And spikes will fire if $U(t)$ exceeds the threshold V_{th}. Moreover, t and n represent the indices of the time step and n-th layer, respectively. Specifically, $\Theta(\cdot)$ represents the Heaviside function. Notice that Eq. 4 is non-differentiable, whose gradients are approximately achieved following. The following derivatives of the surrogate function can be used for approximation.

$$\frac{\partial S^i_{t+1,n}}{\partial U^i_{t+1,n}} = \frac{1}{a} \operatorname{sign}\left(\left|U^i_{t+1,n} - V_{\text{th}}\right| < \frac{a}{2}\right) \tag{5}$$

where a is a defined coefficient for controlling the width of the gradient window and $a = 1$ is set in our experiment for better results. This surrogate function makes only the neurons whose membrane potentials close to the firing threshold receive nonzero gradients during backpropagation. More precisely, the above spiking neurons model can be trained by spatio-temporal backpropagation (STBP) Qiu et al. (2023c), an SNN-version BPTT. The accumulated gradients of loss $\mathcal{L}$ with respect to weights w^j_n at layer n can be calculated as:

$$\begin{cases} \frac{\partial \mathcal{L}}{\partial S^i_{t,n}} = \sum_j \frac{\partial \mathcal{L}}{\partial U^j_{t,n+1}} \frac{\partial U^j_{t,n+1}}{\partial S^i_{t,n}} + \frac{\partial \mathcal{L}}{\partial U^i_{t+1,n}} \frac{\partial U^i_{t+1,n}}{\partial S^i_{t,n}} \\ \frac{\partial \mathcal{L}}{\partial U^i_{t,n}} = \frac{\partial \mathcal{L}}{\partial S^j_{t,n}} \frac{\partial S^j_{t,n}}{\partial U^j_{t,n}} + \frac{\partial \mathcal{L}}{\partial U^j_{t+1,n}} \frac{\partial U^j_{t+1,n}}{\partial U^j_{t,n}} \\ \frac{\partial \mathcal{L}}{\partial W^j_n} = \sum_{t=1}^{T} \frac{\partial \mathcal{L}}{\partial U^i_{t,n+1}} S^j_{t,n} \end{cases} \tag{6}$$

A.3 The Role of Calligraphy

In *Rite of Zhou (Zhou Li)*, the authority requested noblemen to study six skills among which calligraphy is more important than mathematics. In *FaShuYaoLu*, a critical book of art theory written in the Tang dynasty by ZHANG Yanyuan, the order of importance of art forms is musical instruments, go, calligraphy and painting. The above two statements are more than popular in China and have even become familiar idioms for Chinese people nowadays.

A.4 Ablation Study

Ablations over hyperparameters are very important for SNN-related studies. By adopting different timesteps, the results of CaStySNN slightly fluctuate. Nowadays, we do not fully understand the effect of timesteps over performances. However, it is still clear that CaStySNN can perform better than ANN with relatively small timesteps. The immense advantage in computing consumption always holds even if timesteps increase several times for better performances.

A.5 Training Details

On an Intel Core i7-10710U CPU, the models are implemented using PyTorch Paszke et al. (2019) and SpikingJelly Fang et al. (2023). The time step is 8. All layer's bias is False. The optimizer is Adam Optimizer and its initial learning rate is 0.001.

A.6 Counting on Computing Power

Following the routine Zhu et al. (2022) and taking 45nm CMOS as an example, traditional ANN consumes 4.6pJ for each operation. However, for the same environment, a spiking neuron consumes only 0.9pJ for each spike Horowitz (2014). This paper applies the TorchStat tool Swall0w (2018) to count the overall operations of ANN which costs 45k × 4.6pJ = 2.07×10^5pJ. For CaStySNN (T=2), the ideal cost is 16.8 × 0.9pJ = 15.12pJ, considering random activation of spiking neurons and averaging the result. For our paper, different T causes a linear change in overall operations. However, this represents an extremely ideal scenario. Even though it shares similarities with VTSNN in the counting method Qiu et al. (2023a), the outcomes differ. In the future, applying CaStySNN and all the other SNN-based networks to neuromorphic hardware is urgent to test and solve this problem. Currently, CaStySNN retains good characteristics that make it suitable for implementation on a CPU and relatively easy to comprehend in terms of its structure. These features are particularly beneficial for scholars from liberal arts and fine arts backgrounds.

A.7 PROSPECTIVE FUTURE

- Low-level tasks for SNNs are frontiers and relatively rare (Qiu et al., 2023a). In today's trend of AI large model research, lightweight networks should not be neglected. Many low-level (Zhao et al., 2023) and high-level (Guan et al., 2023) problems are good application prospects for lightweight networks and thus may be extended to SNNs. Another huge benefit is that SNNs are accessible for many commodity CPUs (Meisburger et al., 2023).
- Study of the dynamic process of calligraphy art creation and movement is rare. To the best of our knowledge, the only harbinger is Wang et al. (2022). SNN is born for motion information and temporal data. Adopting an adjusted CaStySNN to recognize calligraphy styles when artworks are being created is a probable application in the future. Hybrid architecture, such as CaSty-SpikingYolo Kim et al. (2020), is worth trying.
- More SNN-based cross-disciplinary study in philology is in progress and we hope it can be competitive with ANN-based works Rizk et al. (2021); Luo et al. (2021). Chinese calligraphy styles have emerged with the development of history. This historical process is similar to how the Phoenician alphabet developed to the Old Hebrew and Aramaic alphabets Whitt (1995). Experiments about this have been designed and will be conducted soon on the concept of transfer learning Ribani & Marengoni (2019). And preliminary dataset is organized from Sadouk (2019) and Rabaev et al. (2020).