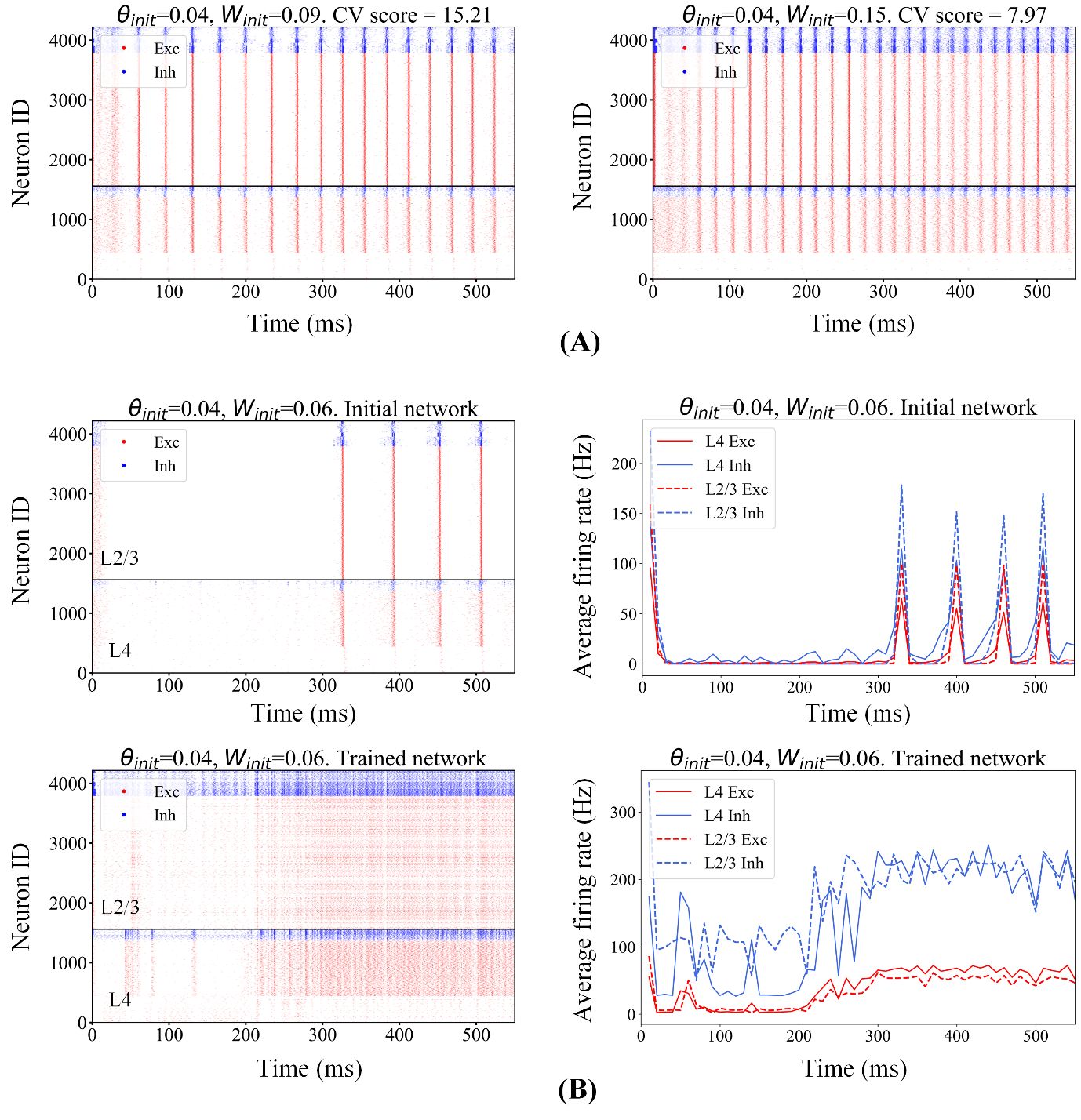
# Supplemental Table 1: Information of 13 neuronal subtypes in the network.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| ID | Subtype | Abbreviation | Location | Type | Size | References |
| 1 | L4 excitatory | Pyr\_SP | L4 | Excitatory | 440 | A,D,E,F,W |
| 2 | L4 excitatory | Pyr\_SS | L4 | Excitatory | 934 |
| 3 | L4 fast spiking | Inh\_FS | L4 | Inhibitory | 94 | A,V,W |
| 4 | L4 low-threshold spiking | Inh\_RSNP | L4 | Inhibitory | 93 |
| 5 | L2/3 pyramidal | Pyr | L2/3 | Excitatory | 2232 | D,F,G,V,H,I,J,P,S,K,N,M,W |
| 6 | PV+ fast-spiking cell | Inh\_FSBS | L2/3 | Inhibitory | 106 | G,S,V,W |
| 7 | PV+ fast-spiking cell | Inh\_FSCH | L2/3 | Inhibitory | 4 |
| 8 | PV+ bursting cell | Inh\_BSPV | L2/3 | Inhibitory | 55 | H,O,W |
| 9 | Martinotti neuron | Inh\_Mar | L2/3 | Inhibitory | 64 | P,T,U,I,J,W |
| 10 | VIP+/CR- cell | Inh\_DBC | L2/3 | Inhibitory | 64 | L,O,S,M,I,W |
| 11 | CR+ bipolar cell | Inh\_Bip | L2/3 | Inhibitory | 34 | L,O,S,T,K,N,W |
| 12 | CR+ multipolar cell | Inh\_SBC | L2/3 | Inhibitory | 60 | L,O,S,M,N,W |
| 13 | Neurogliaform cell | Inh\_NG | L2/3 | Inhibitory | 38 | Q,O,R,G,S,W |

\*\* References: (A) Beierlein et al 2003; (B) Gil et al 1999; (C) Bruno & Sakmann 2006; (D) Feldmeyer et al 2002; (E) Helmstaedter et al 2008; (F) Sun et al 2006; (F) Feldmeyer et al 2006; (G) Holmgren et al 2003; (H) Blatow et al 2003; (I) Ali 2003; (J) Kapfer et al 2007; (K) Reyes et al 1998; (L) Rozov et al 2001; (M) Porter et al 1998; (N) Caputi et al 2009; (O) Gupta et al 2000; (P) Fino & Yuste 2011; (Q) Wozny & Williams 2011; (R) Tamas et al 2003; (S) Avermann et al 2012; (T) Packer & Yuste 2011; (U) Pfeffer et al 2013; (V) Koelbl et al 2015; (W) Chao Huang et al 2022.

# Supplemental Figure 1.

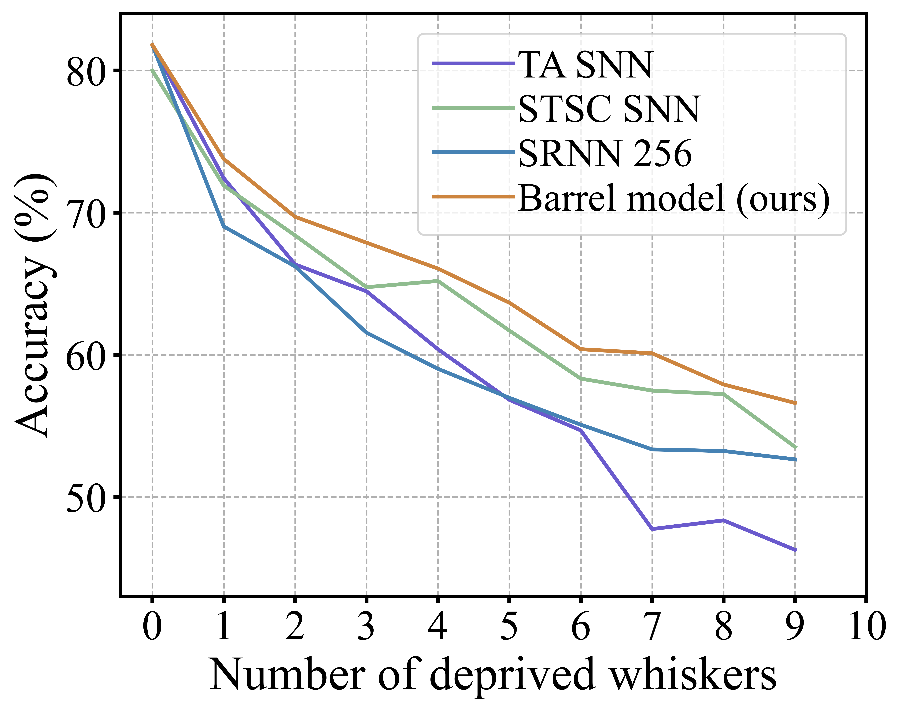


**Supplemental Figure 1: Raster plots of neurons in our model. (A)** Initial networks with different CV scores. It can be observed that networks with lower CV values exhibit more synchronized and intense firing.Synchronous firing occurs because all neurons are initialized with the same parameter values, and aLIF neurons are prone to fire. Moreover, the spike-induced increase in firing threshold renders the firing unsustainable. **(B)** Raster plots and population firing rates of our model before and after training for a same input**.** The synchronous firing dissipated in the trained network. Additionally, the trained network demonstrated higher firing rates in inhibitory neurons compared to excitatory neurons, aligning with neuroscientific research on the excitatory-inhibitory balance[1,2]. Average firing rate is calculated as follows: (total spikes)/(unit time × number of neurons), where unit time is 10 ms.

[1] Peron, Simon P., et al. "A cellular resolution map of barrel cortex activity during tactile behavior." Neuron 86.3 (2015): 783-799.

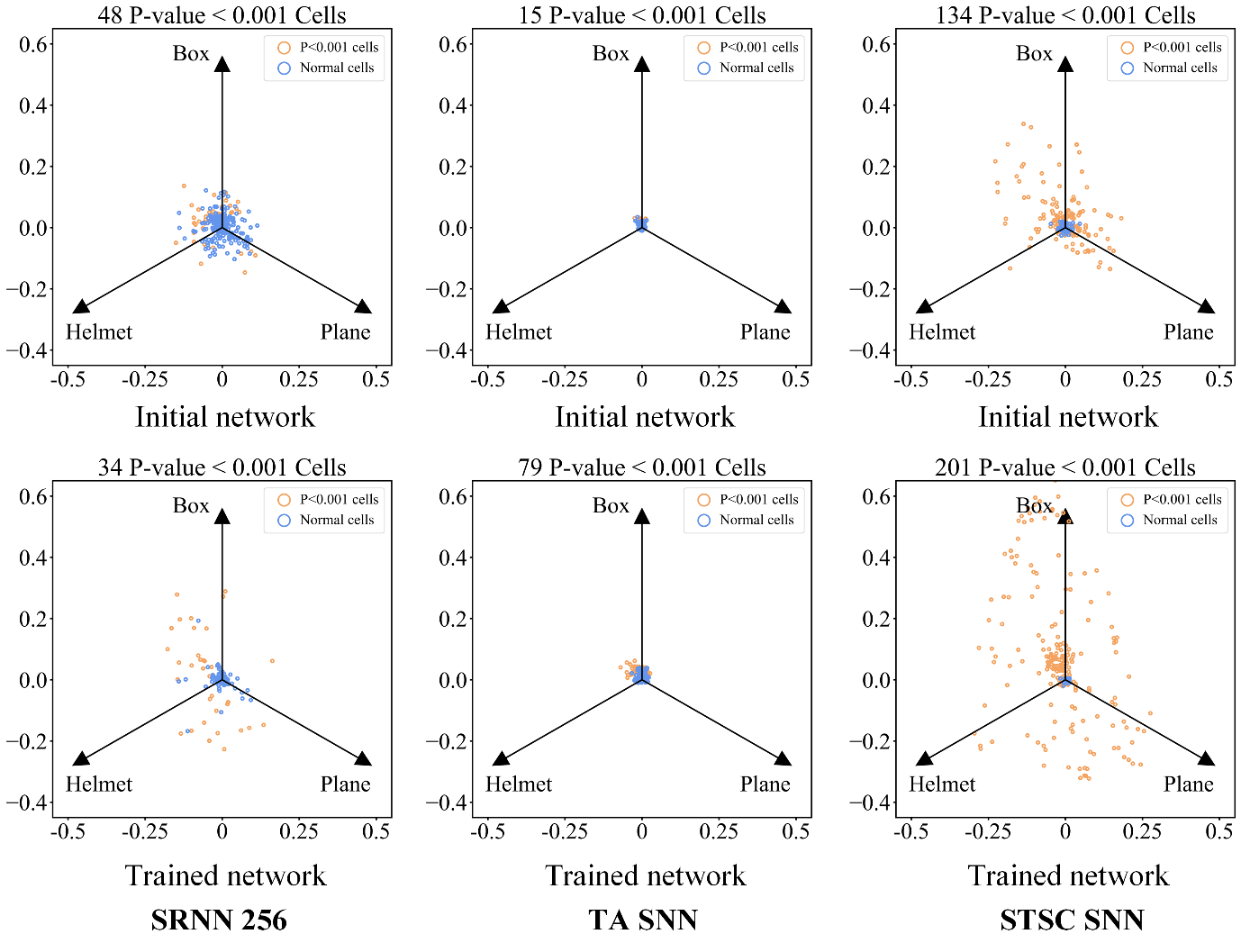
[2] Petersen, Carl CH, and Sylvain Crochet. "Synaptic computation and sensory processing in neocortical layer 2/3." Neuron 78.1 (2013): 28-48.

# Supplemental Figure 2.



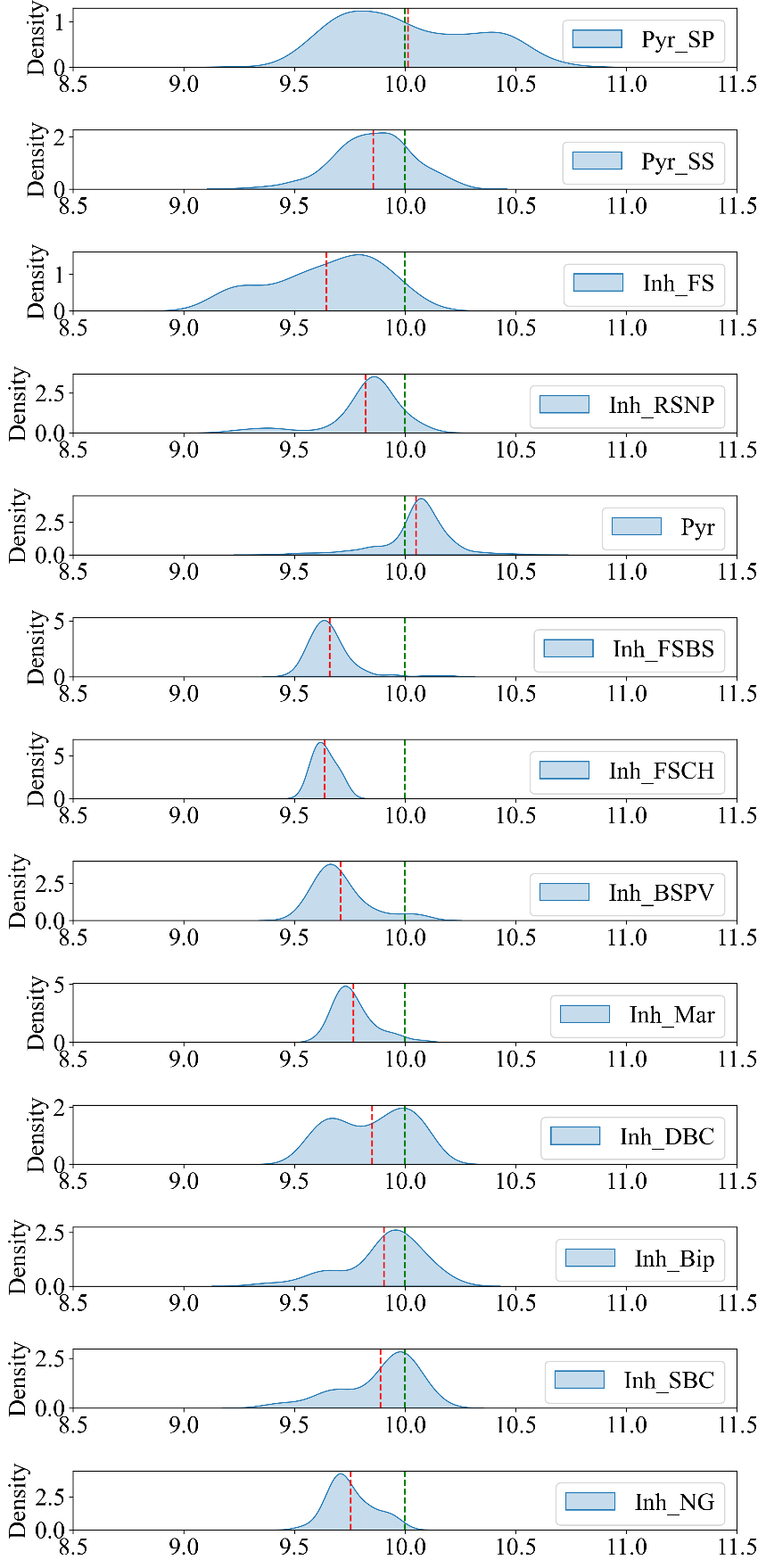
**Supplemental Figure 2: Whisker deprivation experiment results corresponding to Tab. 2.**

# Supplemental Figure 3.



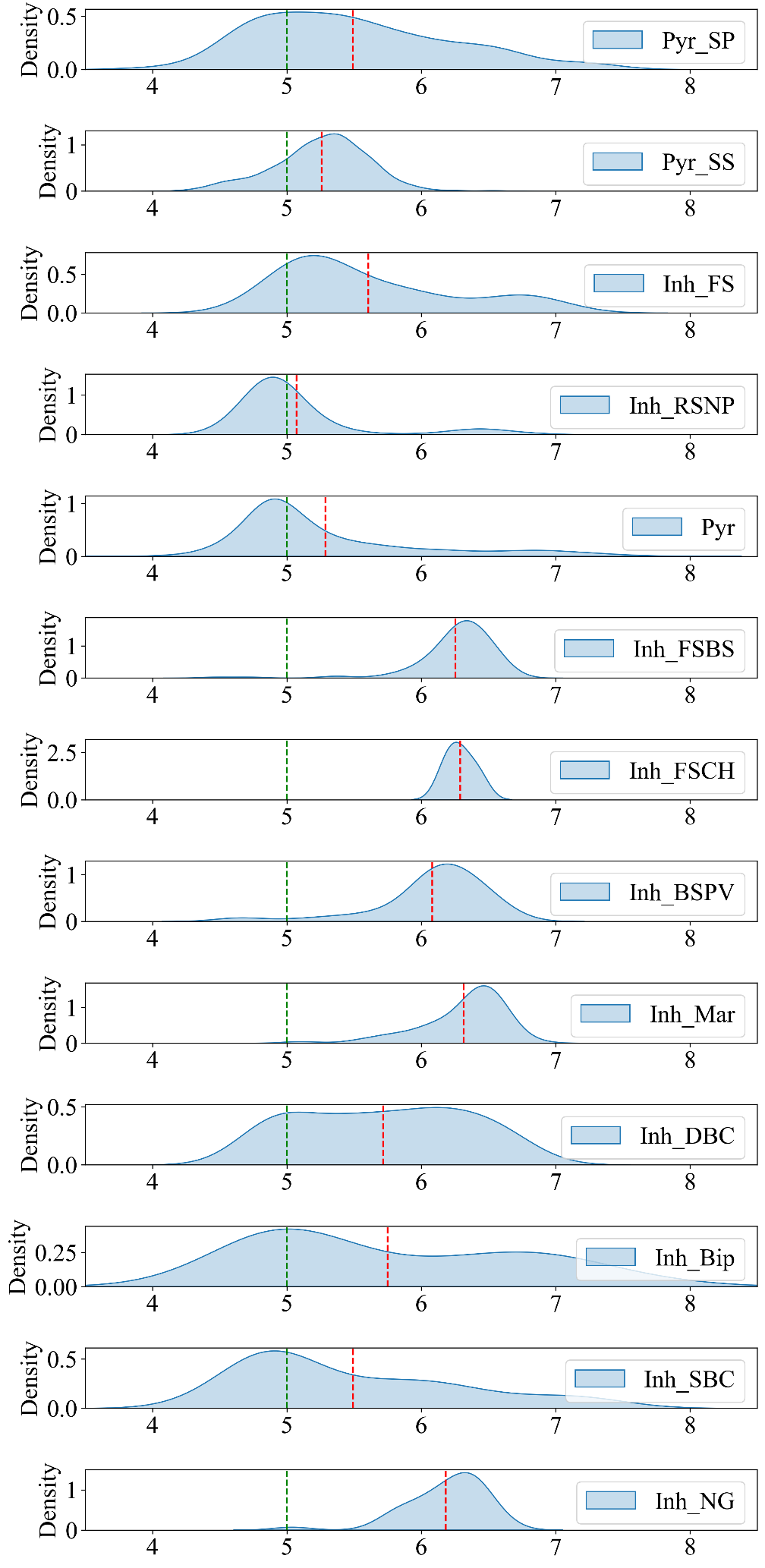
**Supplemental Figure 3: Measured the firing selectivity of three comparative SNNs using the same method described in Fig. 4.** The total number of spiking neurons in these three SNNs are 256, 259, and 271, respectively. The first two models did not exhibit significant firing preferences before or after training, indicating that this is not a ubiquitous phenomenon. The STSC SNN has a significant firing preference in half of its neurons prior to training, whereas our network developed such preferences post-training. Furthermore, compared to the STSC SNN, the neurons in our network are more concentrated in their clustering.

# Supplemental Figure 4.



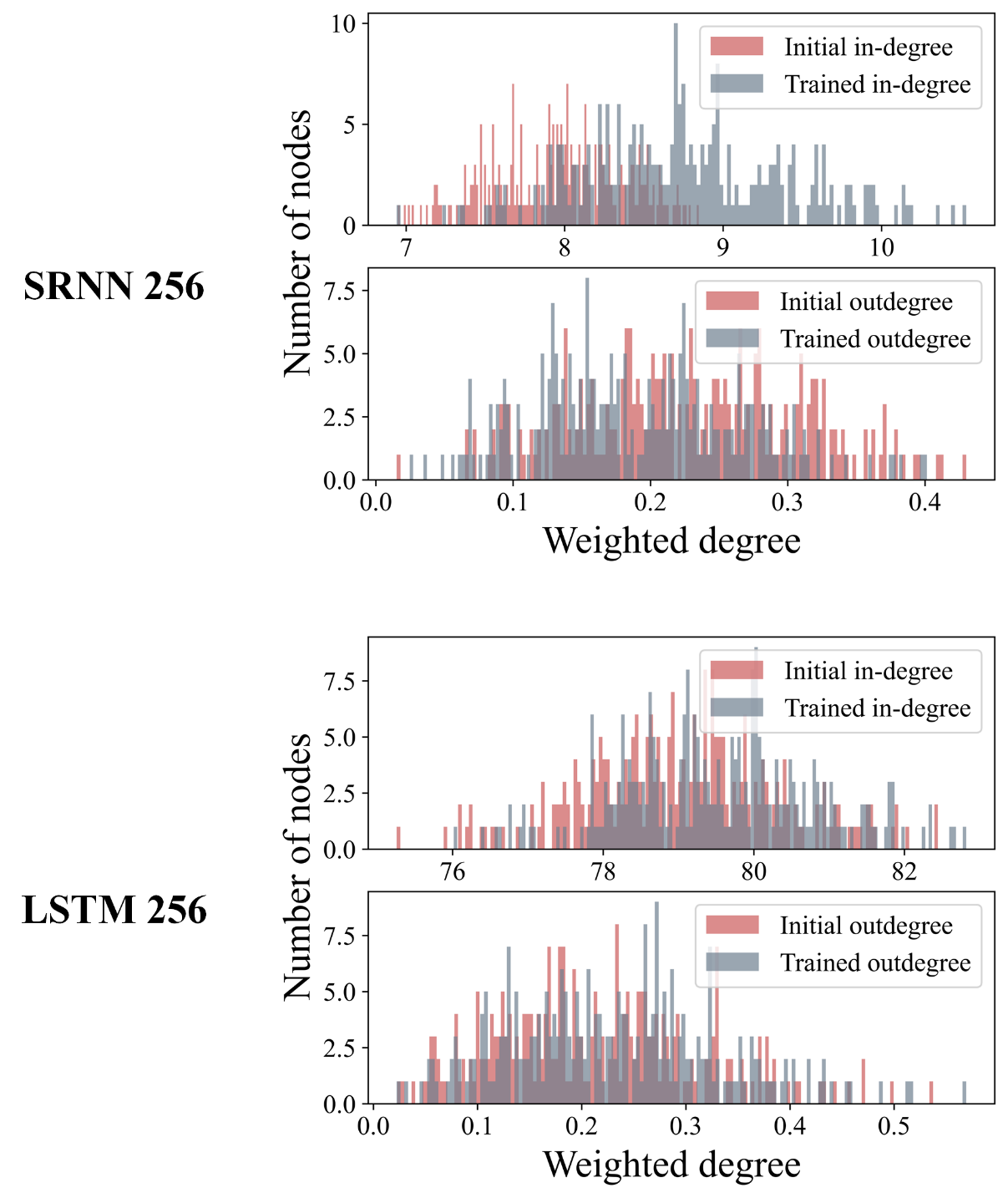
**Supplemental Figure 4: Membrane potential time constants of 13 neural subtypes after training.**

# Supplemental Figure 5.



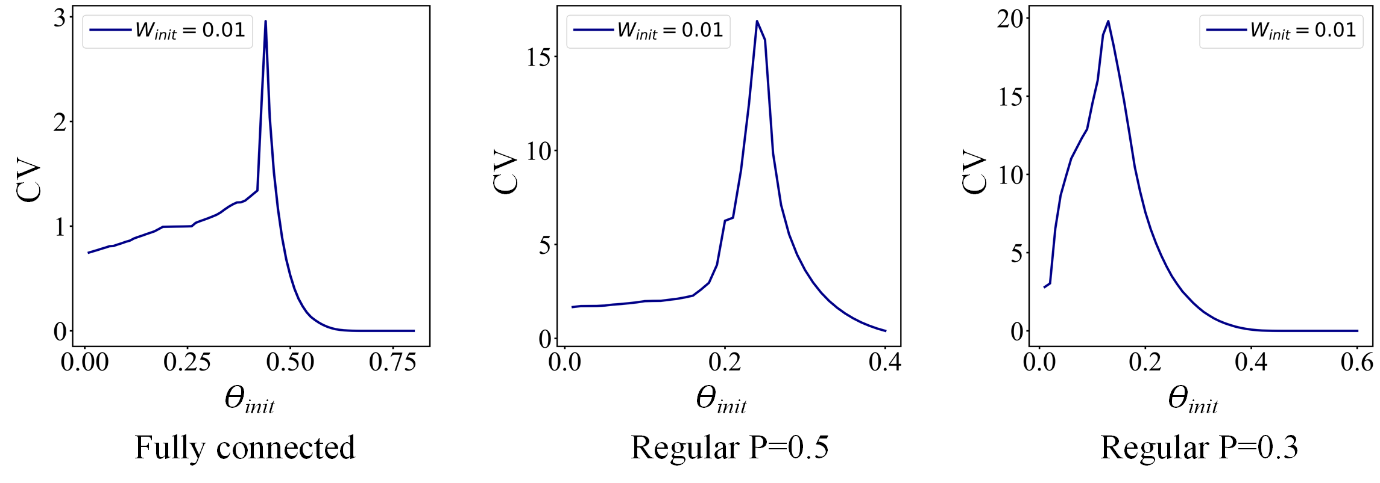
**Supplemental Figure 5: Firing threshold time constants of 13 neural subtypes after training.**

# Supplemental Figure 6.



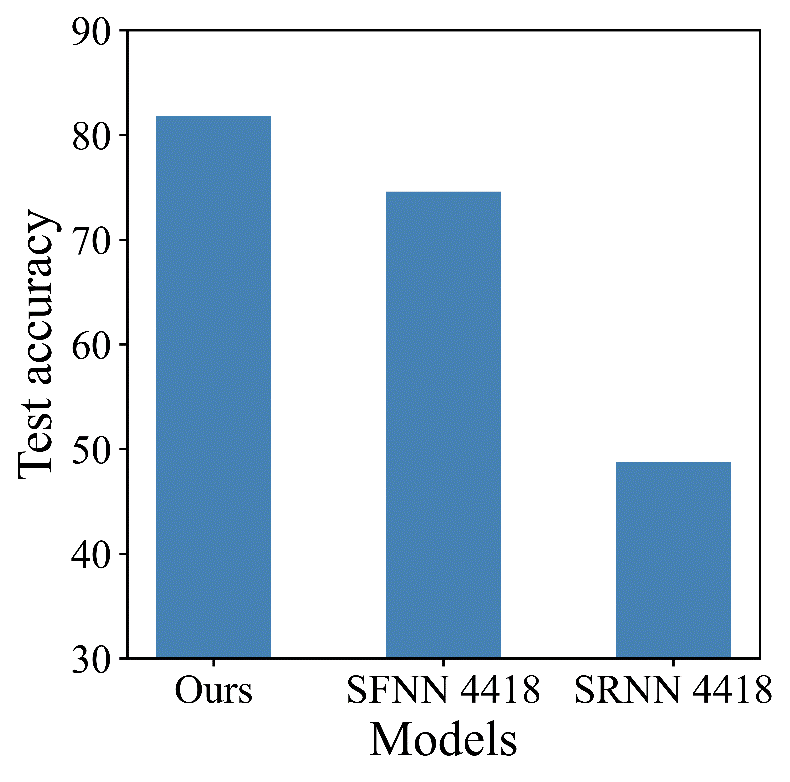
**Supplemental Figure 6: Weighted degree distribution in SRNN 256 and LSTM 256 models, utilizing the methodology illustrated in Fig. 6A.** Due to the presence of negative values in the weights of SRNN 256 and LSTM 256 models, we summed the absolute values of the weights to determine the weighted degree. It can be observed that the weighted degree distribution before and after training is relatively uniform, without exhibiting a long-tail effect similar to that observed in our model.

# Supplemental Figure 7.



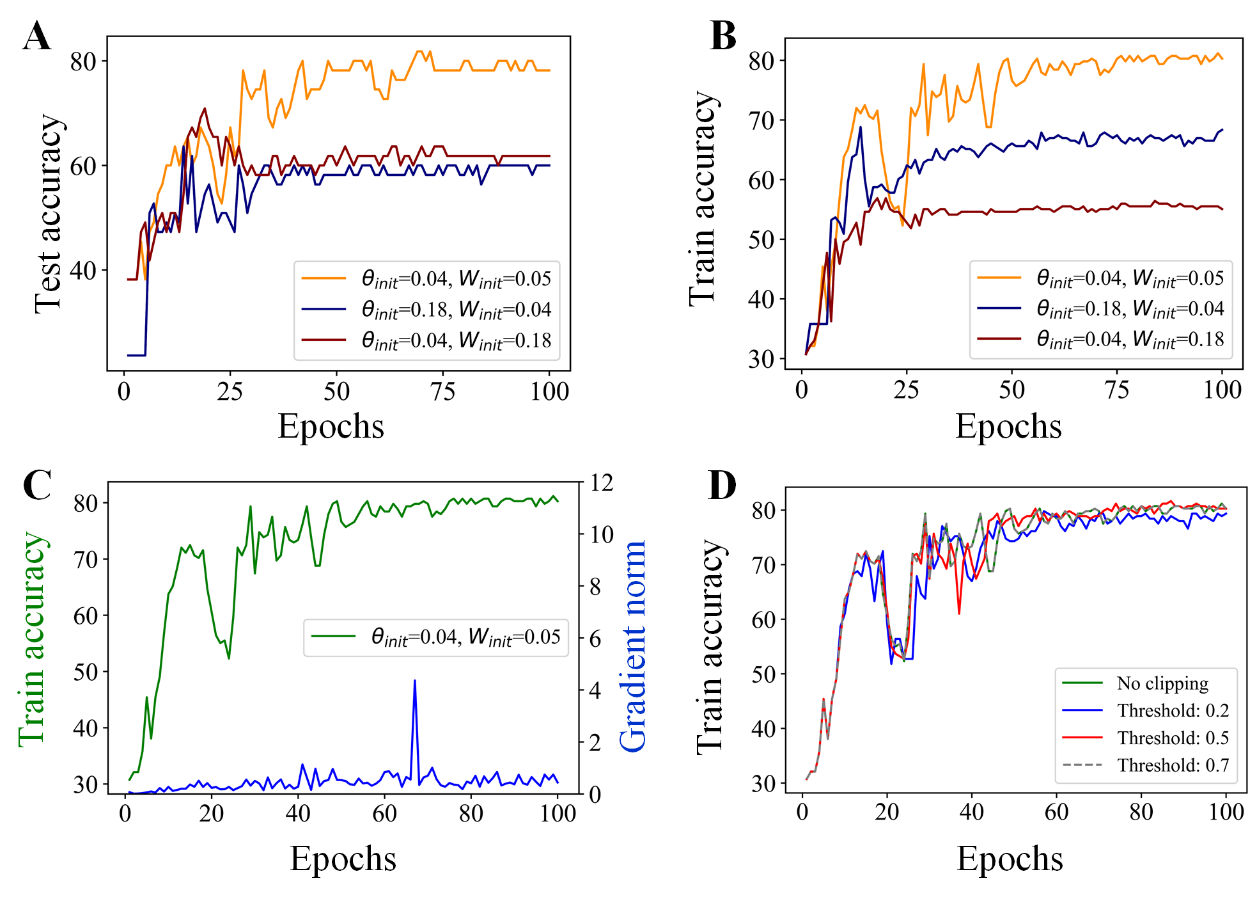
**Supplemental Figure 7: CV measure for three connection configurations in Fig. 6B to determine initial parameters.** The selected initial parameters (θinit, Winit) are (0.44, 0.01), (0.24, 0.01), and (0.13, 0.01), respectively.

# Supplemental Figure 8.



**Supplemental Figure 8: Comparison with simple SNNs of equivalent neuronal scale.** The SRNN was constructed following the methodology of Yin et al., 2020, and the SFNN is a LIF neuron network without recurrent connections. Both networks match our model in terms of neuronal scale and read-in/read-out pathways. The results indicate that the performance of our model is not derived from its neuronal scale.

# Supplemental Figure 9.



**Supplemental Figure 9: The impact of gradient clipping on network training. (A)** Same as Figure 2C in the main text. **(B)** Training accuracy of the models in (A). **(C)** Changes in the norm of the gradient during the model training process. **(D)** The effect of several gradient clipping on the model training process in (C). It can be observed that our biologically constrained model exhibits fluctuations in the early stages of training, and simple gradient clipping does not work effectively on it.