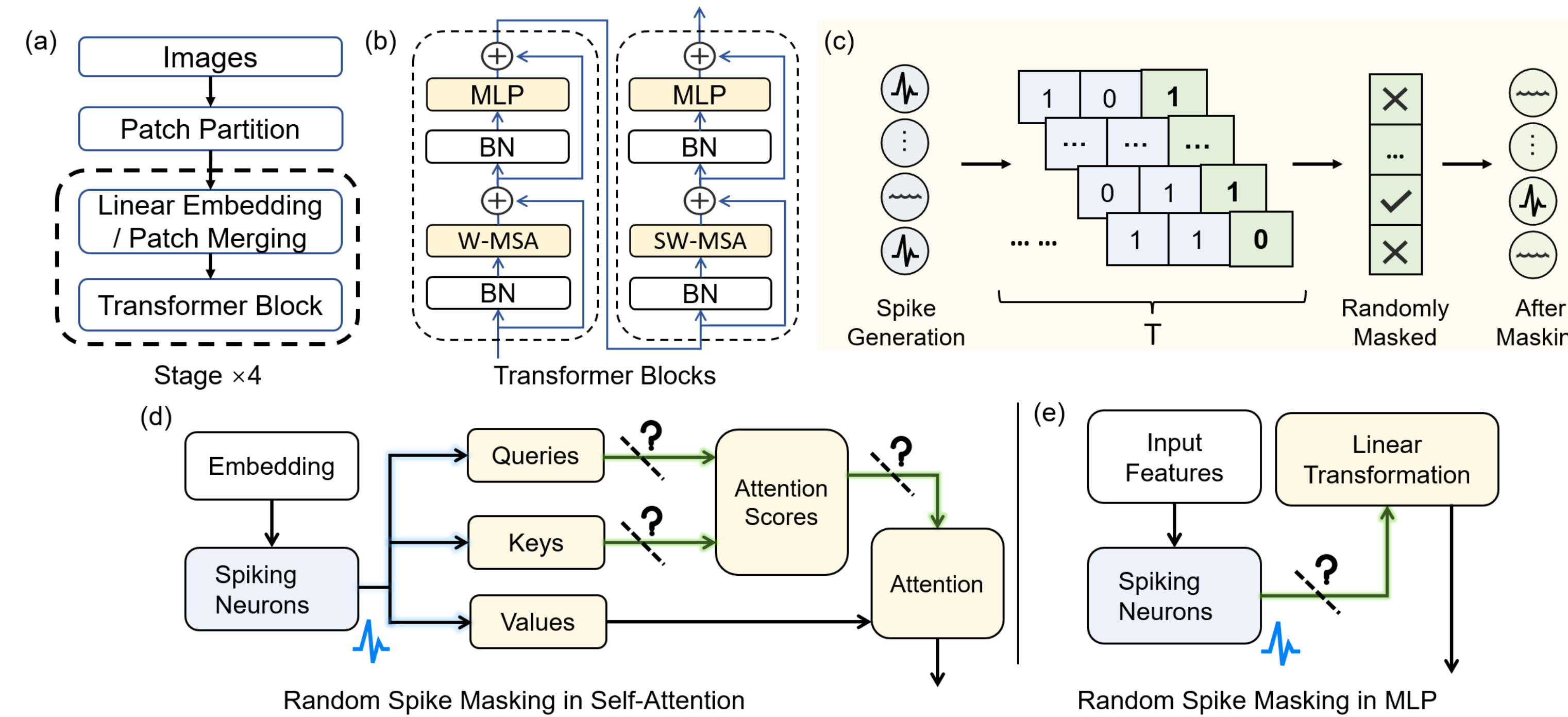


Motivation

- **Performance Gap between ANNs and SNNs:** SNNs are efficient at processing sparse data on neuromorphic hardware but currently lag behind ANNs in performance on complex tasks.
- **High delay and energy consumption of ANN-to-SNN conversion method:** ANN-to-SNN conversion methods convert pre-trained ANNs into SNNs for better performance while requiring more simulation time steps, with increased power consumption to reduce conversion error.

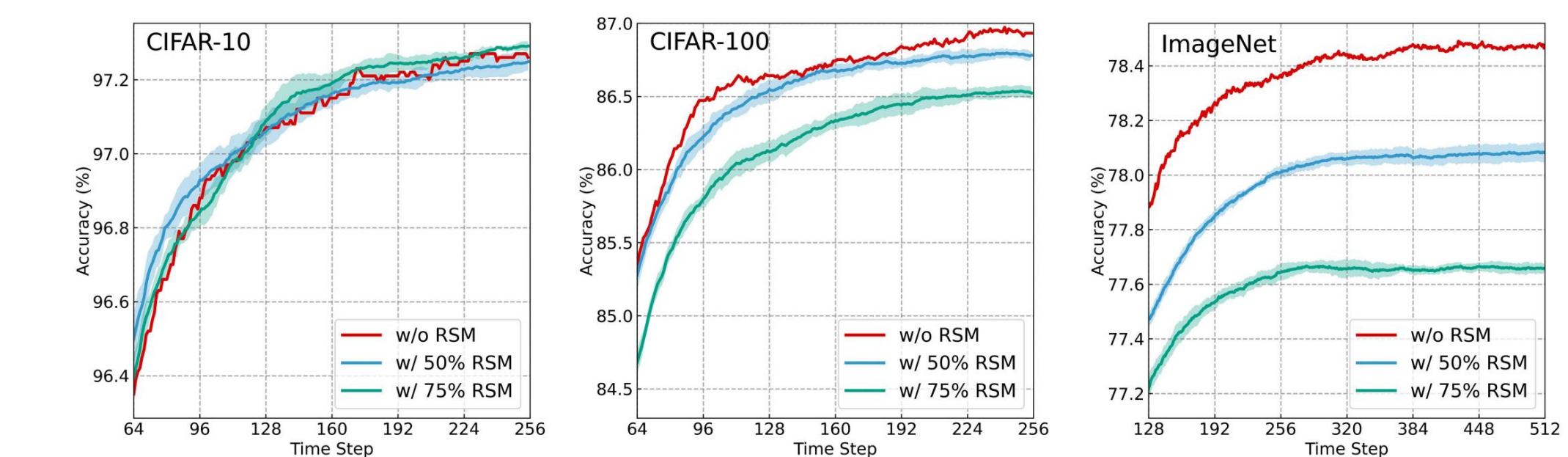
Methods

Masked Spiking Transformer Architecture with Random Spike Masking Method

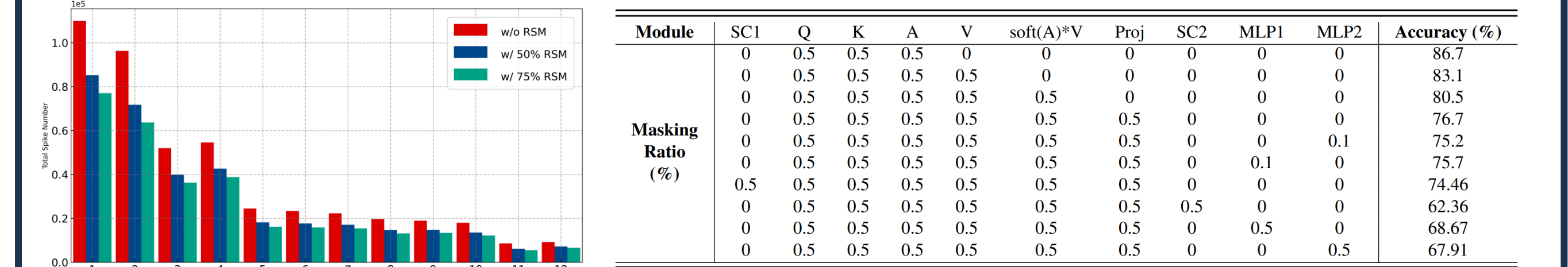


Conclusion

- 1) Implementing self-attention via ANN-to-SNN conversion achieves SOTA accuracy on CIFAR-10, CIFAR-100 and ImageNet, surpassing existing methods by 1.21%, 7.3% and 3.7%.
- 2) The MST model with RSM for randomly prunes input spike reduces power, while differentiating the layer-wise masking ratios can more effectively remove redundancy, as blocks have varying impact to overall performance.



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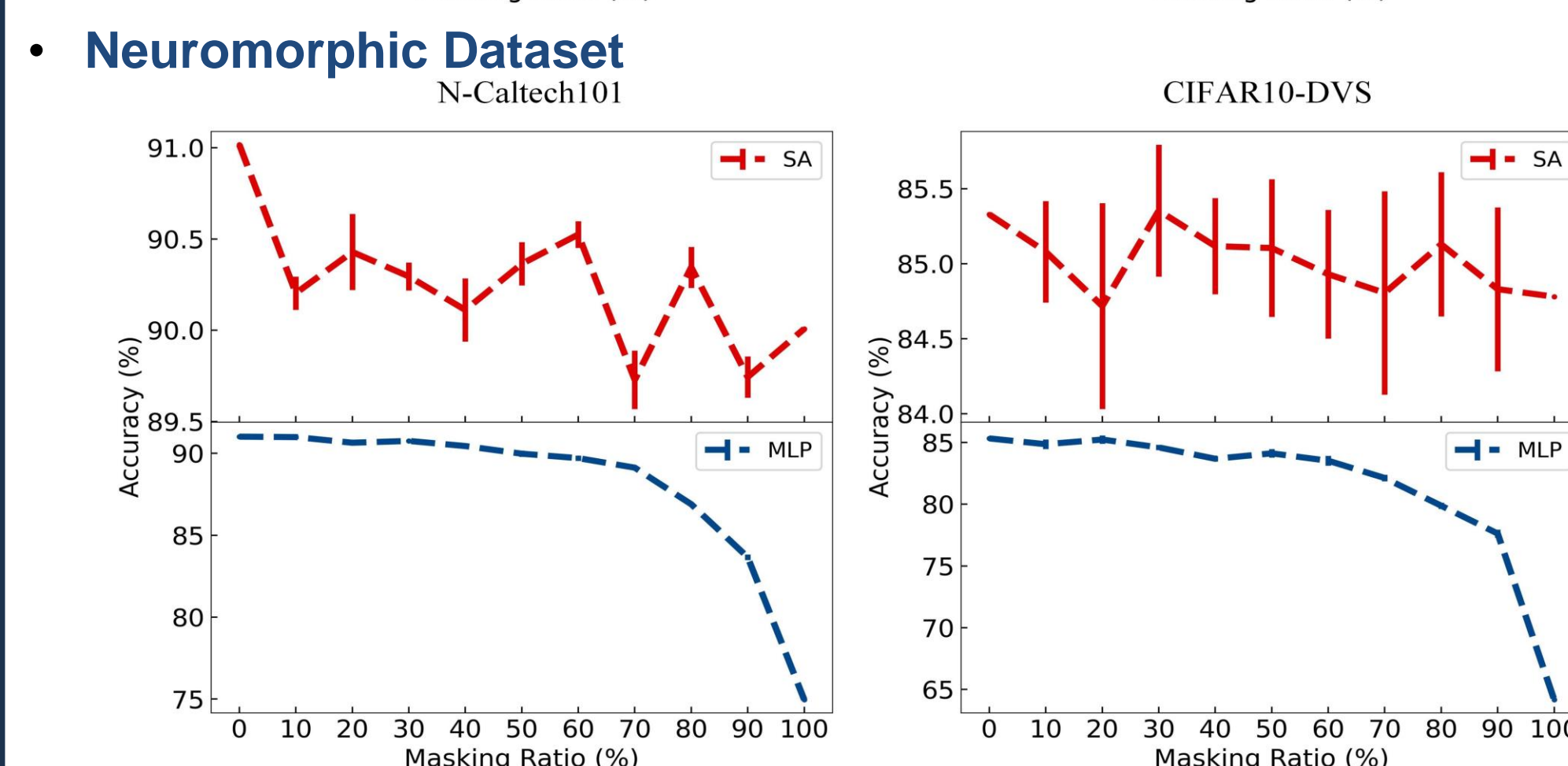
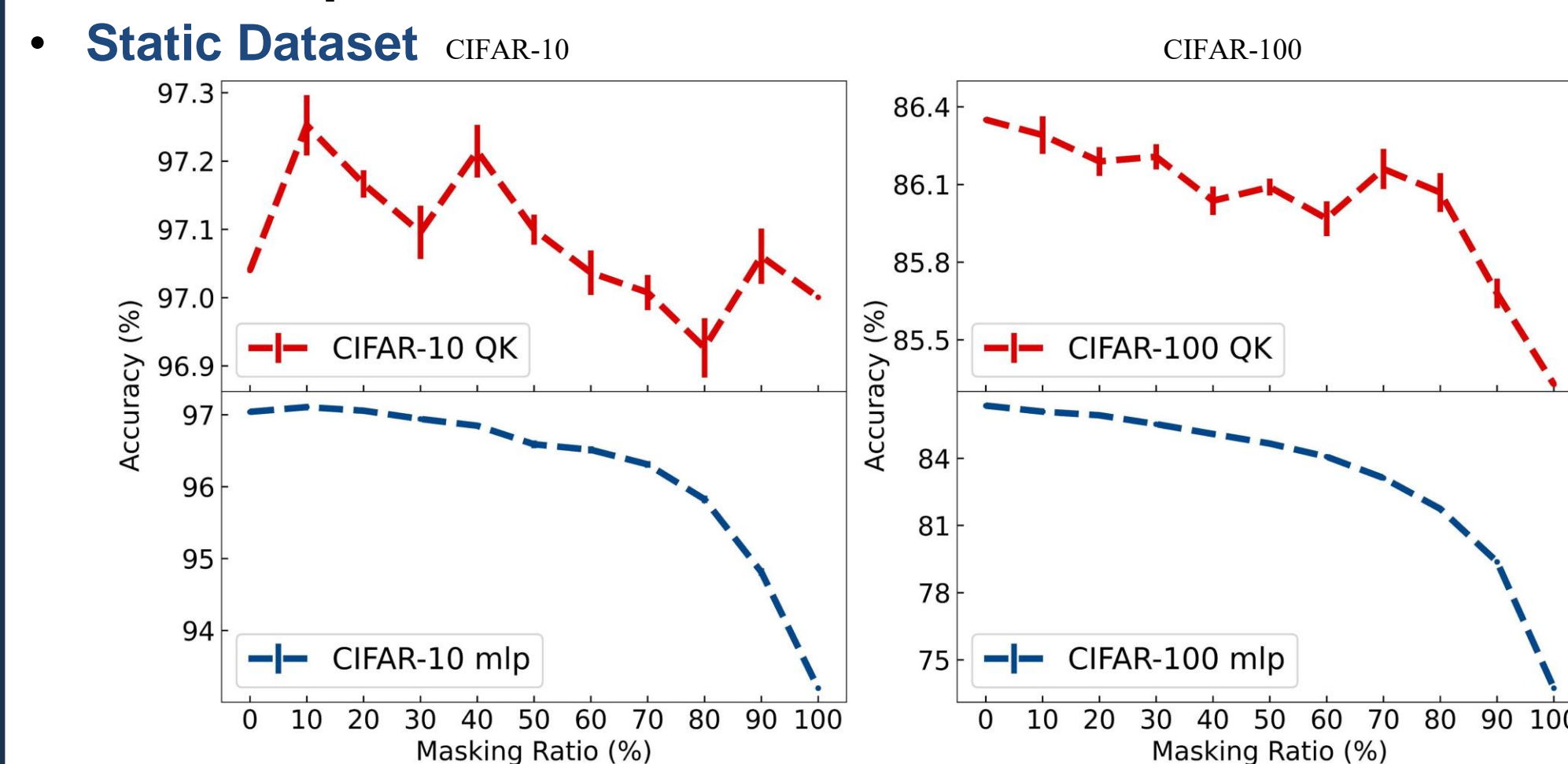


Contributions

- **Masked Spiking Transformer based on ANN-to-SNN conversion methods:** the first exploration of fully implementing the self-attention mechanism in SNNs using ANN-to-SNN conversion methods
- **Random Masking Method for improving energy efficiency:** bio-inspired spike pruning to reduce redundant synaptic operations

Results

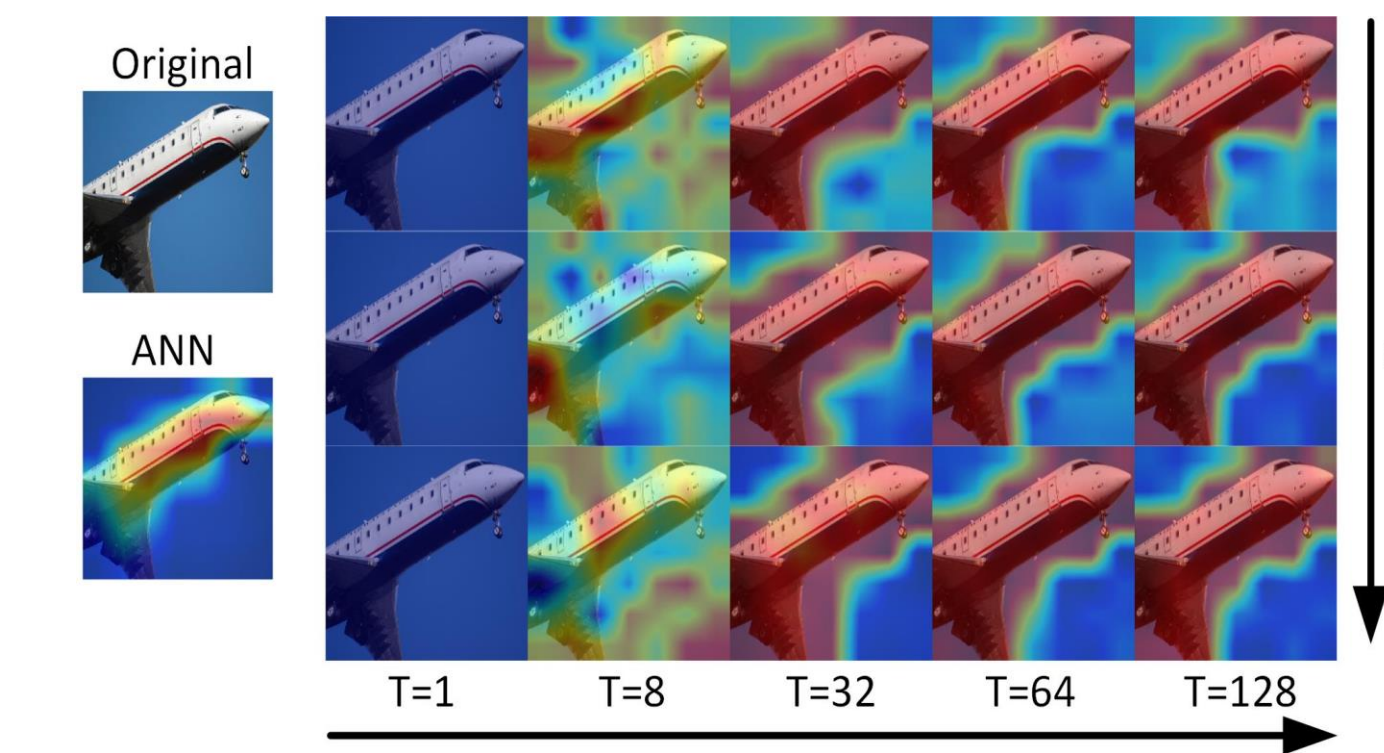
- 1) The MST model that combines self-attention mechanism and ANN-to-SNN conversion methods achieves SOTA top-1 accuracy on both static and neuromorphic dataset.
- 2) The RSM method reduces redundant spike operations while keeping model performance over a certain range of mask rates. For instance, the RSM method reduces MST model power by 26.8% at a 75% mask rate with no performance drop.



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Model	Random Ratio	P (α Watts)	Accuracy (%)
MST	0%	3.9G (×1)	97.27 (+0)
	50%	3.2G (×0.82)	97.25 (-0.02)
	75%	2.9G (×0.74)	97.29 (+0.02)
ResNet-18	0%	58.2M (×1)	96.48 (+0)
	50%	40.7M (×0.70)	92.88 (-3.60)
	75%	34.1M (×0.58)	82.68 (-13.80)
VGG-16	0%	24.4M (×1)	95.46 (+0)
	50%	18.9M (×0.77)	89.56 (-5.90)
	75%	16.7M (×0.68)	79.09 (-16.37)

Models with varying mask rates focus on similar object regions at the same time step, as shown by the red outlines.



Evaluation

- The performance of the **Masked Spiking Transformer model** was evaluated on both static and neuromorphic datasets.
- The effectiveness of the **Random Spike Masking method** was evaluated across various masking configurations and model architectures, using spike count as an indicator of energy efficiency.

Future work

- 1) Investigating the methodology for reducing conversion errors at extremely low time steps could help improve the performance of converted SNNs.
- 2) Optimizing the masking policies could expand the acceptable masking range without compromising performance.
- 3) Applying the RSM method to directly train SNNs could further optimize energy use, making SNNs more practical for real-world deployment.

Acknowledgements

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