A Comparative Analysis of Artificial Neural Networks(ANN) and Spiking Nerual Networks(SNN)

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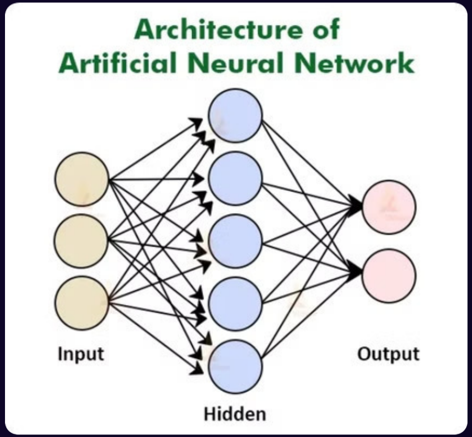
Artificial Neural Network (ANN)

Loosely inspired by biological neurons

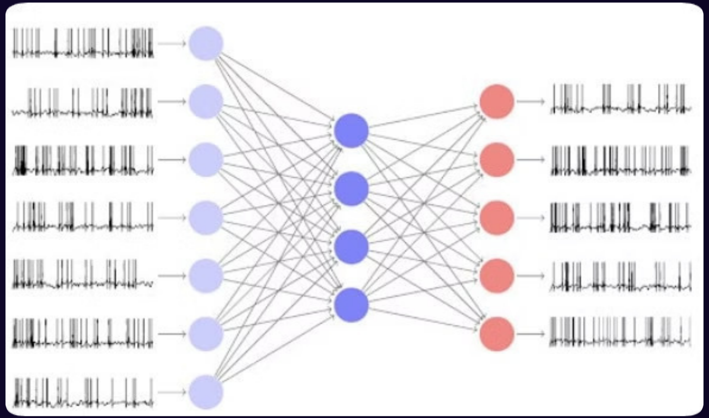
- Key Components: Neurons, Weights, Activation functions, Layers.
- Training: Backpropagation & Gradient Descent.
- Applications: Image recognition, NLP, Reinforcement learning.
- Challenge: Temendous power consumption



What is a Spiking Neural Network (SNN)?

Biologically accurate Neural Network

- Mimics real neurons
- Models synaptic delays and membrane potential
- Uses discrete spikes instead of continuous activations
- Trained using algorithms like Spike Time Dependent Plasticity (STDP), Backpropogation Through Time (BPTT)



Leaky Integate and Fire (LIF) Neuron

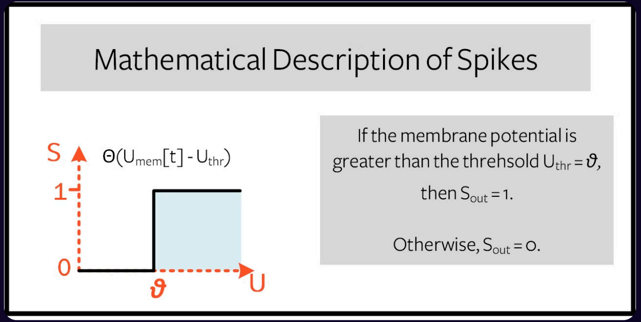
- Basic activation function of SNN
- U[t] - membrane potential
- X[t] - Input Spike train
- W - weights
- beta - decay constant (hyperparameter)
- S[t] - Output spike from neuron

$$U[t+1] = \underbrace{\beta U[t]}_{decay} + \underbrace{WX[t+1]}_{input} - \underbrace{R[t]}_{reset}$$

$$I_{in}[t] = WX[t]$$

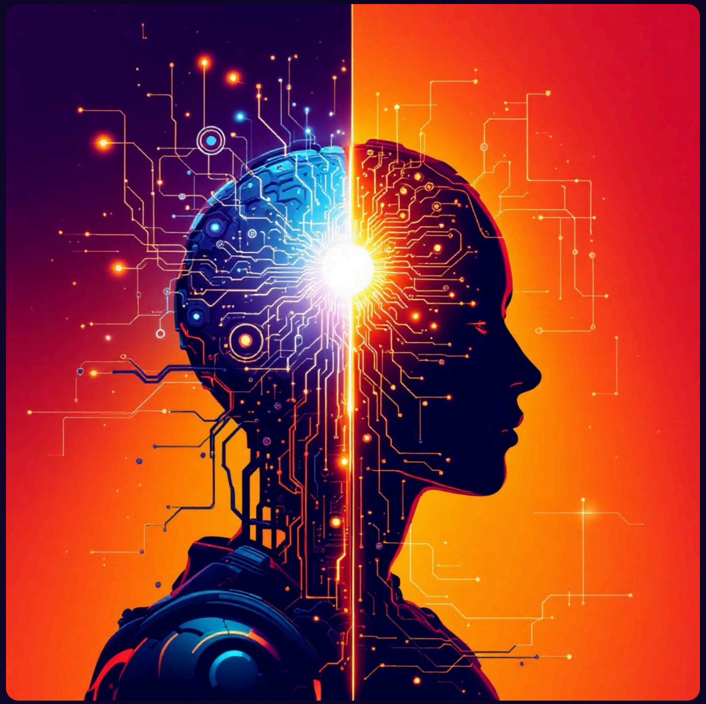
$$X[t] \rightarrow \ input\ spikes$$

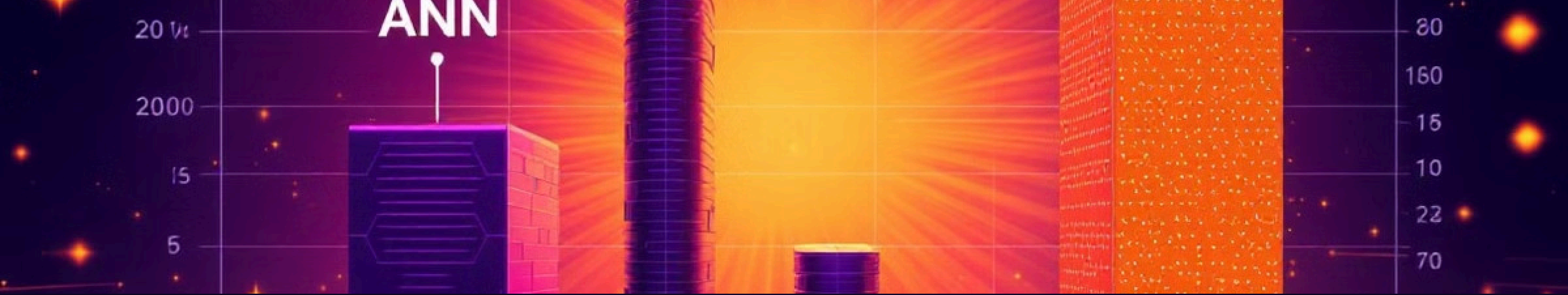
$$S[t] = \begin{cases} 1, if\ U[t] > U_{thr} \\ 0, \quad otherwise \end{cases}$$



Why do we need SNN?

- ANNs consume tremendous power
- ANNs are loosely inspired by the brain.
- Brain is the most efficient computer
- More biologically accuracy should give lower power
- SNNs model real neurons more accurately (synaptic plasticity, energy efficiency).
- SNNs better represent real brain dynamics





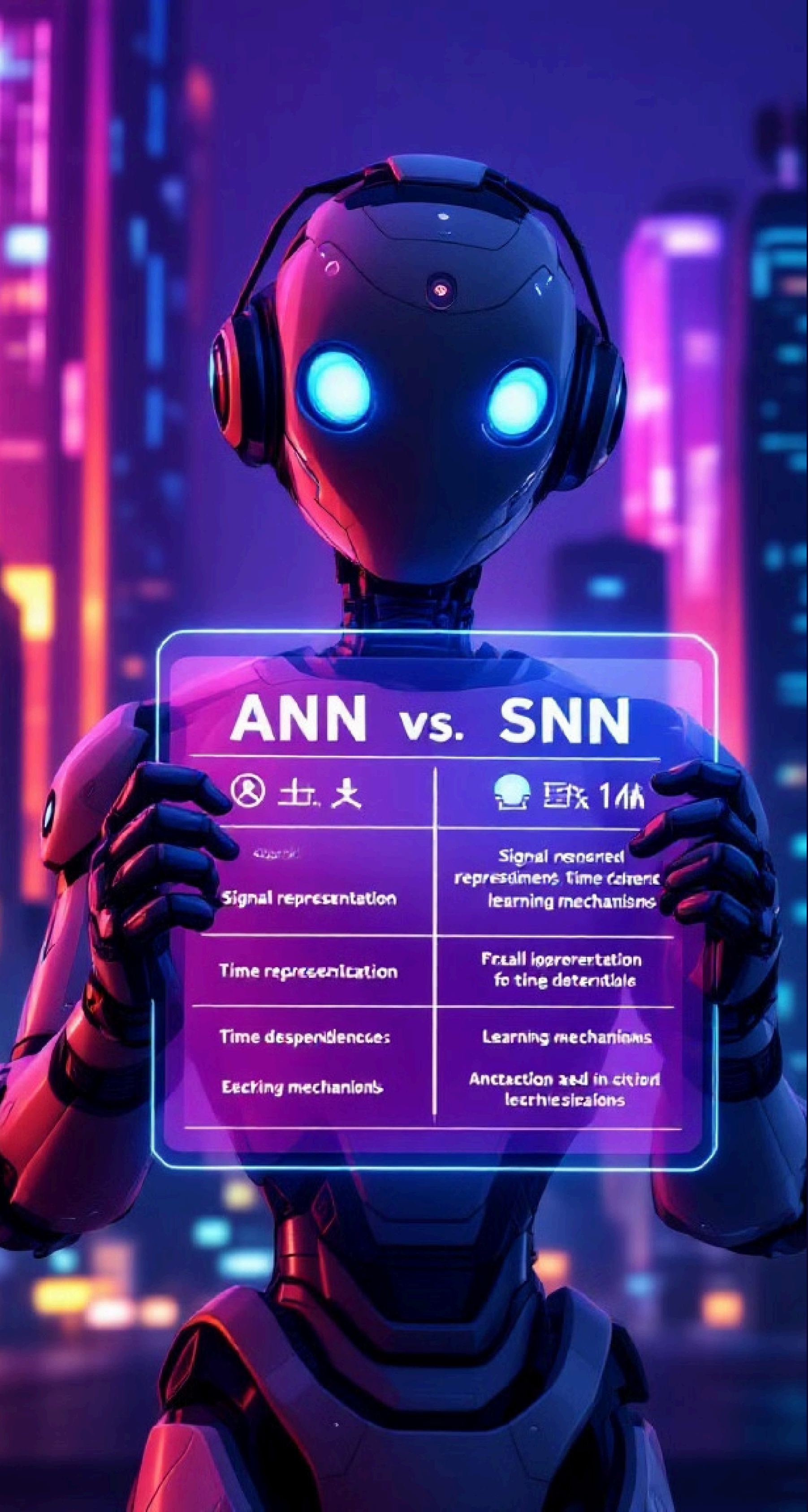
Computational Efficiency and Power Consumption

Energy Efficiency

- **ANNs** require large matrix multiplications → **high power**.
- **SNNs** use event-driven processing → **low power**.

Computational Demands

- Specialized neuromorphic chips (Intel Loihi, IBM TrueNorth) improve efficiency.



Key Differences Between ANN and SNN

Feature	ANN	SNN
Signal Representation	Continuous values	Discrete spikes
Time Dependence	Time-invariant	Time-dependent
Learning	Backpropagation, Gradient Descent	Backpropogation through time (BPTT), Surrogate gardients
Neuron	Perceptron	Leaky Integate and Fire (LIF)
Actvations	Differentiable	Non-differentiable
Applications	Image recognition, Natural Language Processing (NLP), Reinforcement learning	Edge AI, Real-time sensor processing, Brain-computer interfaces (BCI), Robotics

Goal and Motivation

Objective: To compare ANN and SNNs in terms of accuracy, training time, inference time, and model size

To answer the question "Can currrent frameworks of SNNs deliver its promise of low power computing with sufficent accuracy?

Method

Model Selection

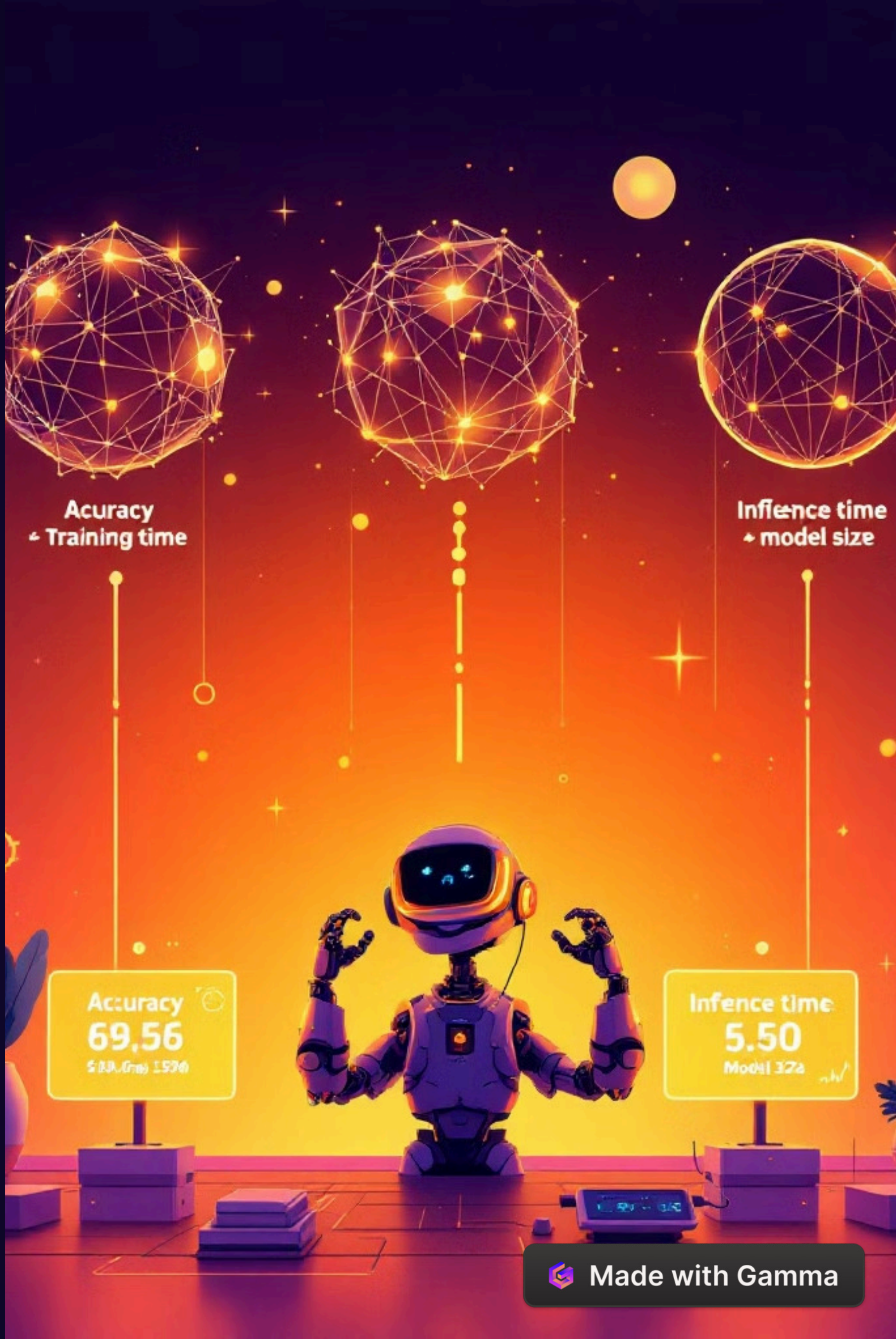
Built feedforward ANN, CNN, and SNN models for comparison.

Dataset Selection

Evaluated performance on MNIST and Fashion MNIST datasets.

Metrics

Compared accuracy, training time, inference time, and model size.



Results

Model	Dataset	Accuracy	Training time	Model size
ANN	MNIST	97.50%	137.82 sec	0.39 MB
CNN	MNIST	99.10%	62.81 sec	1.61 MB
SNN	MNIST	94.22%	67.88 sec	3.04 MB
ANN	Fashion-MNIST	89.25%	294.02 sec	1.04 MB
CNN	Fashion-MNIST	93.08%	285.56 sec	3.69 MB
SNN	Fashion-MNIST	86.20%	835. 68 sec	3.04 MB
ANN	CIFAR10	57.68%	921.66 sec	90.83 MB
ViT	CIFAR10	93.45%	8421.16 sec	327.38 MB

Analysis

Accuracy

SNNs generally exhibit lower accuracy compared to ANNs and CNNs, particularly for complex datasets.

Model Size

SNNs often require larger model sizes compared to ANNs and CNNs, especially for simpler datasets due to temporal discretization of information, which necessitates dividing the data into time steps and storing values

Dataset Complexity

For more complex datasets like Fashion MNIST, SNNs can achieve comparable model sizes to CNNs, suggesting potential for handling challenging tasks while maintaining reasonable resource consumption.

Vision Transformer (ViT)

- Currently best model for image recognition
- Pre-trained and fine tuned ViT —> high accuracy, long fine-tuning time
- Replaced ReLU and GeLU activations in pre-trained ViT with LIF —> doesn't directly work, likely needs fine-tuning

Conclusion

1

ANNs dominate deep learning today

2

SNNs promise low-power, real-time processing but needs more study

3

Hybrid models could shape the future of AI

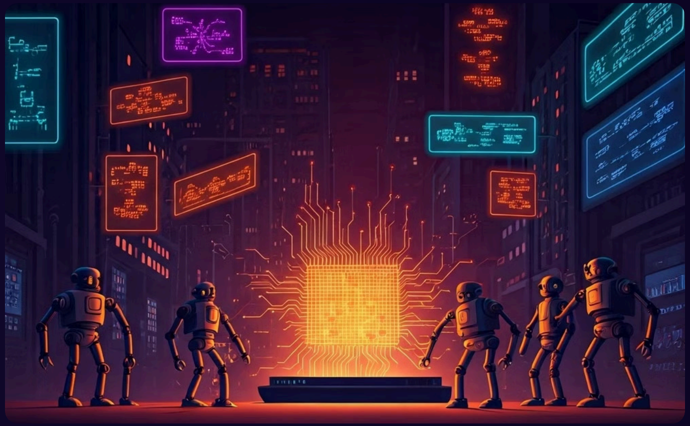
Challenges and Future Directions

ANN challenges

- Energy consumption
- Lack of temporal processing

SNN challenges

- Difficult training
- Lack of software frameworks



Future

- Hybrid AI models combining ANN and SNN

Thank you!

Any Questions?