

# NeuroGlialNet: A Novel Brain-Inspired Architecture with Multi-Layer Astrocyte Networks

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## Abstract

We introduce NeuroGlialNet (NGN), a lightweight neural architecture that models the computational partnership between neurons and astrocytes in the brain. The architecture integrates multi-scale cortical processing with hierarchical astrocyte calcium dynamics through reaction-diffusion PDEs, spatial memory mechanisms, and quantum interference modulation. This concept paper presents the **mathematical foundations** and **architectural innovations** that enable **brain-like** computation in artificial systems. The current implementation has ~ 17,000 parameters (~ 0.066 MB for 32-bit floats), corresponding to a model size of less than 0.1 MB .

**Keywords:** Neural-glial computation, Brain-inspired architecture, Reaction-diffusion systems, Multi-scale processing, Astrocyte networks

## 1. Introduction

NeuroGlialNet is a new type of neural network that treats astrocytes , the brain's most common support cells , as active participants in computation. Unlike traditional networks, which only mimic neuron-to-neuron signaling, NeuroGlialNet also models the calcium signals astrocytes use to influence brain activity across time and space.

Our architecture addresses this fundamental limitation by introducing:

1. **Multi-layer astrocyte networks** with hierarchical calcium dynamics
2. **Reaction-diffusion mathematics** for authentic calcium wave propagation
3. **Quantum interference modulation** inspired by biological coherence effects
4. **Multi-scale cortical processing** suitable for vision/audio tasks

## 2. Mathematical Foundations

## 2.1 Notation and Operators

Spatial grid  $\Omega \subset \mathbb{R}^2$  with indices  $(i,j)$  over  $F \times T$

time steps  $n$  with  $\Delta\tau > 0$ .

$\nabla^2$ : discrete Laplacian operator

$\langle \cdot \rangle_{\text{channels}}$ : channel mean

$R_{\{F \times T\}}$ : bilinear resize.

SiLU, tanh, sigmoid are standard activations.

## 2.2 Astrocyte Calcium Dynamics (single layer form)

### Continuous Reference Model

The spatiotemporal dynamics of the system are governed by a reaction–diffusion equation. In this implementation, clearance ( $\mu$ ), stochastic noise ( $\zeta$ ), and threshold terms are omitted. The governing partial differential equation (PDE) is expressed as:

$$\partial u / \partial \tau = D \nabla^2 u + r u (1 - u/\kappa) + \alpha J$$

where  $u$  represents the state variable,  $D$  is the diffusion coefficient,  $r$  is the intrinsic growth rate,  $\kappa$  is the carrying capacity, and  $\alpha J$  denotes an external input term.

### Numerical Scheme

To simulate the system, we employed an explicit forward Euler finite-difference method. The update rule for the discretized state variable is:

$$u^{n+1}_{\{i,j\}} = u^n_{\{i,j\}} + \Delta\tau [ D (\nabla^2 u)^n_{\{i,j\}} + r u^n_{\{i,j\}} (1 - u^n_{\{i,j\}}/\kappa) + \alpha J^n_{\{i,j\}} ]$$

where  $\Delta\tau$  is the time step, and the superscripts  $n$  and  $n+1$  represent successive time steps.

### Discretization of the Laplacian

The Laplacian operator was discretized differently across layers:

#### *Layers 1–2 (3×3 stencil):*

$$(\nabla^2 u)_{\{i,j\}} = u_{\{i-1,j\}} + u_{\{i+1,j\}} + u_{\{i,j-1\}} + u_{\{i,j+1\}} - 4u_{\{i,j\}}$$

This formulation assumes unit grid spacing, with scaling absorbed into  $D$ , and zero-padding boundary conditions.

#### *Layer 3 (5×5 kernel):*

A more spatially extended Laplacian was applied using the kernel:

$$K = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 2 & 1 & 0 \\ 1 & 2 & -16 & 2 & 1 \\ 0 & 1 & 2 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} / 4$$

$$[0, 1, 2, 1, 0],$$

$$[1, 2, -16, 2, 1],$$

$$[0, 1, 2, 1, 0],$$

$$[0, 0, 1, 0, 0]] / 4$$

with padding size 2 to preserve dimensions.

### Stability Considerations

To ensure practical numerical stability, the update increment  $\Delta$  was clamped to the interval  $[-0.08, 0.08]$ , while the state variable  $u$  was constrained to the range  $[0, 1.8\kappa]$ .

## 2.3 Three-Layer Astrocyte Network

### Architecture

We implemented a hierarchical astrocyte network consisting of three layers ( $\ell = 1, 2, 3$ ). Each layer has an associated diffusion coefficient  $D^{(\ell)}$ , which is treated as a learnable parameter and initialized as:

$$D^{(\ell)} = D_0 / 2^{(\ell-1)}$$

where  $D_0$  is the base diffusion constant. Neural injection  $J^{(\ell)}$  is obtained by channel-averaging the output of a convolutional neural network (CNN) and resizing to match the spatial resolution of each layer.

Coupling between layers is strictly top-down, with higher layers influencing the dynamics of lower layers through learned convolutional operators.

### Governing Equations

The dynamical update for each astrocytic layer is described by the following reaction-diffusion equations:

**Layer 1:**

$$\partial u^{(1)}/\partial \tau = D^{(1)} \nabla^2 u^{(1)} + r u^{(1)}(1 - u^{(1)}/\kappa) + \alpha^{(1)} J^{(1)}$$

**Layer 2:**

$$\partial u^{(2)}/\partial \tau = D^{(2)} \nabla^2 u^{(2)} + r u^{(2)}(1 - u^{(2)}/\kappa) + \alpha^{(2)} J^{(2)} + \psi K_2[u^{(1)}]$$

**Layer 3:**

$$\partial u^{(3)}/\partial \tau = D^{(3)} \nabla^2 u^{(3)} + r u^{(3)}(1 - u^{(3)}/\kappa) + \alpha^{(3)} J^{(3)} + \psi K_3[u^{(2)}]$$

Here,  $u^{(\ell)}$  denotes the astrocytic state variable for layer  $\ell$ ,  $r$  is the intrinsic activation rate,  $\kappa$  is the saturation capacity, and  $\alpha^{(\ell)}$  scales the strength of neural injection. The operator  $K_\ell[\cdot]$  represents a learned  $3 \times 3$  convolutional kernel applied to the preceding layer, with coupling strength  $\psi = 0.05$ .

### Spatial Memory Mechanism

Each layer  $\ell$  maintains a long-term spatial memory variable  $S_\ell$ . This memory is updated at every timestep according to an exponential moving average:

$$S_\ell \leftarrow \beta S_\ell + (1 - \beta) \langle u_\ell \rangle_{\text{batch}}$$

where  $\langle u_\ell \rangle_{\text{batch}}$  denotes the mean activation of the layer over the minibatch, and  $\beta \approx 0.95$  controls the memory retention. To encourage stability and context preservation, a fraction ( $0.1 S_\ell$ ) is added to the neural injection  $J^{(\ell)}$  during updates.

## 2.4 Quantum-Inspired Interference

We introduce a quantum-inspired interference mechanism designed to capture oscillatory and phase-dependent modulation within the system. The formulation operates on two inputs:

$$\theta \in [0,1]^{F \times 1} \text{ and}$$

$$\tau \in [0,1]^{1 \times T},$$

representing feature-space and temporal coordinates, respectively.

The envelope function is defined as:

$$b(\theta) = a \exp(-\alpha\theta) \sin(k\theta) \cos(m\theta)$$

where  $a$  is the amplitude,  $\alpha$  controls exponential decay, and  $k$  and  $m$  determine the oscillatory frequency components.

### Phase and Component Interactions

For each component  $i = 1 \dots n$  (with  $n = 6$  in this implementation), the phase is computed as:

$$\phi_i = 2E_i \tau + \delta_i \theta$$

where  $E_i$  represents the energy coefficient and  $\delta_i$  the phase shift.

The interaction terms between input components  $u_a$  and  $u_b$  are represented as:

$$A_i = \text{Re}(u_b)_i \text{Re}(u_a)_i + \text{Im}(u_b)_i \text{Im}(u_a)_i$$

$$B_i = \text{Im}(u_b)_i \text{Re}(u_a)_i - \text{Re}(u_b)_i \text{Im}(u_a)_i$$

These terms encode amplitude and phase relationships across channels.

### Interference Aggregation

The aggregated real and imaginary interference terms are then computed as:

$$X = \sum_i [ A_i \cos(\phi_i) + B_i \sin(\phi_i) ]$$

$$Y = \sum_i [ -A_i \sin(\phi_i) + B_i \cos(\phi_i) ]$$

The resultant interference magnitude is obtained as:

$$S = \sqrt{(X^2 + Y^2 + \varepsilon)}$$

where  $\varepsilon$  is a small constant to ensure numerical stability.

### Output Normalization

The raw interference response is defined as:

$$r = b(\theta) \cdot S$$

This response is then normalized:

$$\hat{r} = (r - \min) / (\max - \min + \varepsilon)$$

Finally, the quantum-inspired modulation term is given by:

$$M_{\text{qim}} = 0.9 + 0.2 \hat{r}$$

This normalization constrains the modulation output to the interval  $[0.9, 1.1]$ , ensuring stable integration into the broader model dynamics.

## 3. Neural Architecture Design

### 3.1 Multi-Scale Cortical Processing

The input tensor is denoted as

$$X \in \mathbb{R}^{B \times C \times H \times W},$$

where  $B$  is the batch size,  $C$  is the number of channels, and  $H \times W$  represents spatial dimensions. To capture features at multiple receptive fields, three parallel convolutional branches are applied with kernel sizes  $\kappa \in \{3, 5, 7\}$ . Each branch computes:

$$F_{\kappa}(X) = \text{SiLU}(\text{GN}(\text{Conv}_{\kappa}(X)))$$

where  $\text{Conv}_{\kappa}$  represents a convolution with kernel size  $\kappa$ ,  $\text{GN}$  is group normalization, and  $\text{SiLU}$  is the activation function. The outputs of all branches are concatenated along the channel dimension and fused through a  $1 \times 1$  convolution followed by  $\text{GN}$  and  $\text{SiLU}$ .

### 3.2 Neural–Glial Integration

The architecture incorporates bidirectional coupling between neural and glial subsystems.

#### Neural $\rightarrow$ Glial Injection:

For each astrocytic layer  $\ell$ , neural activity is projected into the glial domain as:

$$J^{\wedge}(\ell) = R_{\{F \times T\}}(\langle H^{\wedge}(\ell) \rangle_{\{\text{channels}\}})$$

where  $\langle H^{\wedge}(\ell) \rangle_{\{\text{channels}\}}$  denotes channel-averaged CNN features, and  $R_{\{F \times T\}}$  represents a reshape operator into feature-time space.

The injection strength is scaled by  $\alpha^{\wedge}(\ell) \in [0.01, 0.2]$ .

#### Glial $\rightarrow$ Neural Modulation:

Each glial layer modulates neural activity using fixed weights  $w = [0.5, 0.3, 0.2]$ .

A per-sample normalization function  $N(u)$  rescales activations via min–max normalization. The modulation term for layer  $\ell$  is defined as:

$$M^{\ell}(u^{\ell}) = 1 + 0.4 \tanh(2(N(u^{\ell}) - 0.5))$$

**A spatial variance correction is then applied:**

$$V = \text{AvgPool}_{\{3 \times 3\}}(N(u)) - N(u)$$

$$M_c \leftarrow M^{\ell} + 0.2 V$$

The modulation values are clamped to the interval [0.7, 1.3].

The fused modulation map is obtained by:

$$M = \sum_{\ell} w_{\ell} M_c$$

When **quantum-inspired modulation** (QIM) is enabled, an additional scaling is applied:

$$M \leftarrow \text{clamp}(M \cdot (0.8 + 0.2 \text{sigmoid}(M_{\text{qim}})), 0.7, 1.3)$$

This ensures bounded and stable glial-to-neural modulation.

### 3.3 Attention and Feature Selection

To refine neural representations, a global average pooling operation is applied across spatial dimensions, followed by a two-layer multilayer perceptron (MLP). A sigmoid activation produces channel-wise attention weights, which rescale the pooled feature vector before it is passed into the final classifier MLP.

## 5. Training Methodology

### 4.1 Data Pipeline and Preprocessing

Model inputs are converted into mel-spectrograms, which are normalized per sample and resized via bilinear interpolation to match the astrocytic grid ( $F \times T$ ) described in Section 3.2. To improve robustness,

optional augmentations such as time masking, frequency masking, and mild additive noise are applied. Mini-batches are constructed with labels, and inputs are padded or cropped to preserve aspect ratios while remaining consistent with CNN stride constraints.

### 4.2 Optimization and Scheduling

The training objective combines classification, neural–glial interaction, and smoothness regularization:

$$L = L_{\text{cls}} + \lambda_{\text{int}} L_{\text{int}} + \lambda_{\text{smooth}} L_{\text{smooth}}.$$

- **Classification loss ( $L_{\text{cls}}$ ):** standard cross-entropy applied to predicted class probabilities.

$L_{\text{cls}} = \text{CE}(y, \hat{p})$ , where CE is cross-entropy between labels  $y$  and predicted probabilities  $\hat{p}$ .

- **Interaction loss ( $L_{\text{int}}$ ):** regularizes the neural–glial modulation introduced in Section 3.2, encouraging bounded, informative modulation while discouraging saturation.

Composed of two terms:

- *Saturation penalty:*  $L_{\text{sat}} = \text{mean}[\text{ReLU}(M_{\text{pre}} - 1.3) + \text{ReLU}(0.7 - M_{\text{pre}})]$ , penalizing excursions outside the modulation bounds.
- *Diversity term:*  $L_{\text{div}} = 1 - \text{Var}(N(u))$ , where  $N(u)$  is per-sample min–max normalized calcium activity.
- *Combined:*  $L_{\text{int}} = L_{\text{sat}} + \rho L_{\text{div}}$ , with  $\rho$  a small weighting factor.

- **Smoothness loss ( $L_{\text{smooth}}$ ):** penalizes high-frequency noise in astrocyte calcium dynamics  $u$  using the discrete Laplacian operator defined in Section 2.2, ensuring stability without oversmoothing.

For each astrocyte layer  $\ell$  with Laplacian kernel  $K_\ell$ ,

$L_{\text{smooth}} = \text{mean}_{\{B, \ell\}} [\|K_\ell * u^\wedge(\ell)\|_F^2]$ , where both the  $3 \times 3$  and  $5 \times 5$  Laplacian stencils are applied.

Optimization uses AdamW with weight decay, gradient clipping to a safe norm, and a ReduceLROnPlateau scheduler with patience-based decay. The learning rate is bounded below by a small floor value.

### 4.3 Neural–Glial Rollout Within Training

For each batch, CNN-derived features generate per-layer injections  $J^\wedge(\ell)$ . The three astrocyte layers (Section 2.3) are updated for  $k \geq 1$  explicit Euler steps, using clamping on increments  $\Delta u$ , calcium states  $u$ , and injections  $J$  to maintain stability (Sections 2.2–2.3). The normalized calcium fields are then fused into the modulation map  $M$  (Section 3.2), which modulates neural activations prior to the attention and classification modules (Section 3.3).

Each astrocytic layer also maintains a persistent spatial memory  $S_\ell$ , updated as:

$$S_\ell \leftarrow \beta S_\ell + (1 - \beta) \langle u_\ell \rangle,$$

where  $\beta \approx 0.95$ . This state persists across batches and epochs during both training and evaluation, ensuring consistent modulation statistics.

## 4.4 Evaluation, Checkpoints, and Early Stopping

Validation follows the same neural–glial rollout as training but excludes stochastic augmentations. Checkpoints are saved based on minimum validation loss. Training logs track loss components, learning rate dynamics, calcium statistics, and modulation ranges to confirm values remain within the prescribed  $[0.7, 1.3]$  interval (Section 3.2).

Early stopping is applied if no improvement is observed after a fixed patience interval.

## 5. Architectural Innovations

We propose several architectural innovations that integrate astrocytic reaction–diffusion (RD) dynamics directly into the neural processing pipeline, rather than as a post-hoc modulation. These mechanisms provide stability, multi-scale context propagation, and biologically inspired spatial memory.

### 3.1 In-the-loop astrocyte modulation

A three-layer RD astrocytic stack is embedded directly within the forward pass of the network. For every training batch, calcium dynamics are updated iteratively and fused into a multiplicative spatial modulation map. This map is applied directly to intermediate neural features, thereby influencing attention and classification (Section 4.3), rather than serving as a detached auxiliary signal.

### 3.2 Hierarchical RD with top–down coupling

Astrocytic layers are hierarchically coupled. Each higher layer receives a learned  $3 \times 3$  convolution of the preceding layer with a

fixed gain  $\psi = 0.05$ . This design enables multi-scale spatial context propagation, allowing global and local calcium fluctuations to co-modulate the neural feature space.

### 3.3 Persistent spatial memory

Each astrocytic layer  $\ell$  maintains a persistent state variable  $S_\ell$  through an exponential moving average with decay  $\beta \approx 0.95$ . During each RD update step, a stabilizing injection term equal to  $0.1 \cdot S_\ell$  is added, providing long-term contextual memory. This persistence encodes slow-changing background context and prevents runaway oscillations.

### 3.4 Variance-aware modulation

To emphasize edges and local contrasts, the normalized calcium field  $N(u)$  is refined using a variance-aware contrast operator,  $V = \text{AvgPool}_{3 \times 3}(N(u)) - N(u)$ . The final modulation is clamped within the stability-preserving interval  $[0.7, 1.3]$ , ensuring both expressivity and bounded influence.

### 3.5 Quantum-inspired interference modulation

An optional quantum-inspired interference mechanism is introduced, whereby a bounded factor  $0.8 + 0.2 \cdot \text{sigmoid}(M_{\text{qim}})$  is multiplicatively blended into the modulation map. This term increases the effective dynamic range of astrocytic modulation while maintaining stability through bounded scaling.

### 3.6 Stability-by-design constraints

To prevent numerical instabilities, astrocytic updates employ a forward Euler discretization with explicit clamping. Per-step increments are restricted to  $\Delta u \in [-0.08, 0.08]$ , states are constrained to  $u \in [0, 1.8\kappa]$ , and injection strengths  $J$  as well as scaling parameters  $\alpha^\ell$  are limited to  $[0.01, 0.2]$ . Diffusion coefficients  $D^\ell$  are initialized as  $D_0 / 2^{\ell-1}$ , providing progressively slower diffusion in higher layers.

### 3.7 Physically grounded discretization

Reaction–diffusion operators are implemented with exact  $3 \times 3$  and normalized  $5 \times 5$  Laplacians, employing zero-padding at the boundaries and unit lattice spacing. Diffusion scaling is fully absorbed into  $D^\ell$ , providing a consistent physical grounding across layers.

### 3.8 Lightweight CNN backbone

Neural feature extraction is handled by a compact CNN backbone composed of parallel  $3 \times 3$ ,  $5 \times 5$ , and  $7 \times 7$  convolutional branches, followed by Group Normalization and SiLU activations. Tiny residual blocks and channel attention are used for efficiency. Fusion of glial modulation across the three layers employs fixed combination weights  $w = [0.5, 0.3, 0.2]$ .

### 3.9 Stateful inference

During evaluation, both astrocytic memory states  $S_\ell$  and calcium field statistics persist across batches. This ensures that test-time behavior remains consistent with training-time dynamics, aligning modulation statistics and reducing distributional mismatch.

## Conclusion

NeuroGlialNet advances brain inspired design by capturing the role of astrocytes through reaction diffusion dynamics, hierarchical coupling, and quantum inspired interference. This framework combines biological realism with computational strength and points toward new directions for artificial intelligence that more closely reflect how the brain computes. Importantly, the architecture achieves strong performance while remaining extremely lightweight, <0.1 MB .

This efficiency makes NGN particularly well suited for deployment in mobile, embedded, and edge AI systems where memory and energy resources are limited, opening possibilities for biologically grounded intelligence in real world applications.

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