Model-Physcosis: Technical Architecture Document

1. Architecture Overview (MultiHeadBDHNet)

The **Model-Physcosis** is built upon the **MultiHead Baby Dragon Hatchling (BDH) Network**, a specialized Spiking Neural Network (SNN) designed for temporal graph classification. Unlike traditional RNNs or Transformers, it leverages **Hebbian Plasticity** to "learn" the connectivity of the brain dynamically as it processes an fMRI scan.

1.1 Core Components

The model consists of three distinct computational blocks:

1. **Multi-Head BDH Layer (`MultiHeadBDHLayer`)**: The core plasticity engine.
2. **Trajectory Attention Pooling (`TrajectoryPooling`)**: A dynamic temporal aggregator.
3. **Fused Classification Head**: A dense layer combining structural and dynamic features.

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2. In-Depth Component Analysis

A. Multi-Head Plasticity Layer

Instead of fixed weights, the network maintains **Evolving Synaptic Weights** (W_t) that change for every time step t in the fMRI sequence.

- **Input**:
  - `x` : Spike train sequence (B, T, N), where $N=105$ (Brain Regions).
  - `w_init` : Initial Functional Network Connectivity (FNC) matrix (B, N, N).
- **Mechanism**: The layer operates **4 Parallel Plasticity Heads**, each with a distinct **Decay Rate (α)**:
  - **Head 0 ($\alpha=0.9$)**: Long-term memory (stable connectivity).
  - **Head 1 ($\alpha=0.7$)**: Medium-term adaptation.
  - **Head 2 ($\alpha=0.5$)**: Short-term adaptation.
  - **Head 3 ($\alpha=0.1$)**: Rapid transient response.

Hebbian Update Rule: For each head h, the synaptic weight matrix $W^{(h)}$ updates as: $$ W^{(h)}_{t+1} = \alpha_h \cdot W^{(h)}_t + \eta \cdot (x_t \otimes x_t^T) $$

   - α_h: The learnable decay factor for head h.
   - η: The learnable learning rate (plasticity coefficient).
   - $x_t \otimes x_t^T$: The outer product of activations (Hebb's rule: *neurons that fire together, wire together*).

- **Output**:

   - **Final Weights (W_{final})**: A tensor of shape $(B, 4, 105, 105)$ representing the *learned brain topology* after viewing the entire scan.
   - **Output Sequence (y_{seq})**: A sequence $(B, T, 4, 105)$ representing the dynamic brain states.

B. Trajectory Attention Pooling

To capture the temporal dynamics of the "thought process" (trajectory), we use an attention mechanism rather than simple averaging.

- **Input**: The sequence of hidden states y_{seq}.
- **Mechanism**:
   1. **Query (Q)**: A global learnable vector representing "what important moments look like."
   2. **Key/Value (K, V)**: Projections of the sequence y_{seq}.
   3. **Attention**: Computes a weighted sum of all time steps based on relevance to the Query. $$ \text{Context} = \text{Softmax}(\frac{Q K^T}{\sqrt{d}}) V $$
- **Advantage**: This allows the model to focus on specific moments of high synchronous activity (e.g., a sudden burst of connectivity) while ignoring noise.

C. Feature Fusion

The model combines two complementary views of the data for classification: 1. **Structural View**: The flattened final weights (W_{final}), representing the **"Brain Wiring Diagram"** learned over the session. 2. **Dynamic View**: The pooled trajectory context, representing the **"Flow of Activity"**.

These are concatenated and passed to a dense classifier: $$ \text{Logits} = \text{MLP}(\text{Concat}(\text{Flatten}(W_{final}), \text{Pooled}(y_{seq}))) $$

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3. Utilizing the BDH Advantage

The model exploits the BDH architecture to solve the specific challenges of fMRI analysis:

1. solving the Non-Stationarity Problem

Challenge: Brain connectivity is not static; it changes rapidly (seconds) vs slowly (minutes). **BDH Advantage**: By using **Multi-Head Plasticity with diverse α values**, the model captures **Multi-Scale Temporal Dynamics**. * High α heads capture the stable "traits" of the subject (e.g., Schizophrenia baseline). * Low α heads capture the transient "states" (e.g., momentary thought patterns).

2. Solving the Data Scarcity Problem

Challenge: fMRI datasets are small (hundreds of samples) but high-dimensional. **BDH Advantage**: **Self-Supervised Hebbian Learning**. The effective parameters (weights) are not learned via Gradient Descent but are *generated* by the data itself via the Hebbian rule. The model only learns the *hyperparameters* (α, η) governing this generation. This makes the model extremely **Data-Efficient** and resistant to overfitting compared to an LSTM or Transformer with millions of fixed parameters.

3. Solving the Interpretability Problem

Challenge: Deep learning models are black boxes. **BDH Advantage**: **Explicit Topology**. The final output W_{final} is literally a connectivity matrix. We can inspect this matrix to see exactly which brain regions strengthened their connections during the scan. For example, if Regions A and B have a high weight in W_{final}, it means they fired synchronously throughout the session.

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4. Performance Metrics

Validated Accuracy

Our final model, trained with **Stratified Splitting** and **Weighted Cross-Entropy Loss** to handle class imbalance, achieves:

- **Overall Validation Accuracy**: **62.11%** (Macro-Average: 62.12%)
- **Class-Wise Performance**:
  - **Bipolar Disorder (BP)**: 62.2% Recall, 51.1% Precision.
  - **Schizophrenia (SZ)**: 62.1% Recall, 72.0% Precision.
- **Confusion Matrix (Validation)**:
  - **BP**: 23 Correct / 14 Missed
  - **SZ**: 36 Correct / 22 Missed

Significance: Unlike previous iterations that achieved ~55% by guessing the majority class (SZ), this model is **perfectly balanced**, demonstrating a true ability to discriminate between the two conditions despite the noise and complexity of fMRI data.