Segmentation of Non-Excitable Calcium Patterns

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(Q1) High-level Problem: This project addresses the identification and categorization of complex, subtle calcium signaling patterns in simulated *non-excitable* cells using Genetically Encoded Calcium Indicator (GECI) video data. Existing methods often struggle with the low signal intensity in these cells. We propose developing and fine-tuning a *transformer-based* model for improved cell segmentation and calcium pattern classification.

(Q2) Motivation: Calcium signaling is fundamental to tissue engineering. Analyzing patterns in non-excitable cells offers key insights into intercellular communication and regulation. This project applies cutting-edge deep learning (transformers) to overcome limitations in analyzing biologically significant imaging data, potentially advancing tools for tissue engineering research.

(Q3) Relation to Data Science Life Cycle: Starting from the **Domain problem** (understanding subtle calcium signals), our plan involves **1. Data collection** :simulating GECI videos. **2. Data cleaning and pre-processing,** which is labeling the area of interest. **4. Predictive and/or inferential analysis** by developing and training a transformer model for segmentation (prediction). A critical step is **5. Scrutinization of results** using metrics like IoU and F1 score. The project aims for **6. Interpreting results** to understand biological patterns, potentially **Updating domain knowledge**.

(Q4) High-level Steps: Simulation Code: https://github.com/ygong2501/calcium

1. **Simulate Data:** Generate realistic GECI video datasets. Embed known ground truth calcium patterns (e.g., localized spikes, intercellular propagating waves) for supervised learning.
2. **Model Development & Adaptation:** Implement or fine-tune a suitable transformer architecture to handle spatio-temporal dependencies.
3. **Training & Fine-tuning:** Input will be video frame sequences; outputs will be per-pixel segmentation masks and per-cell classified activity labels or temporal traces. Combinations of Dice/IoU loss for segmentation, cross-entropy or specialized temporal losses for activity classification.
4. **Evaluation**: Dice and IoU for segmentation. Event detection rate (proportion of true events found), and temporal IoU (tIoU) for assessing the temporal accuracy of detected event boundaries.