# Forecasting Morphogenesis in Latent and Image Space

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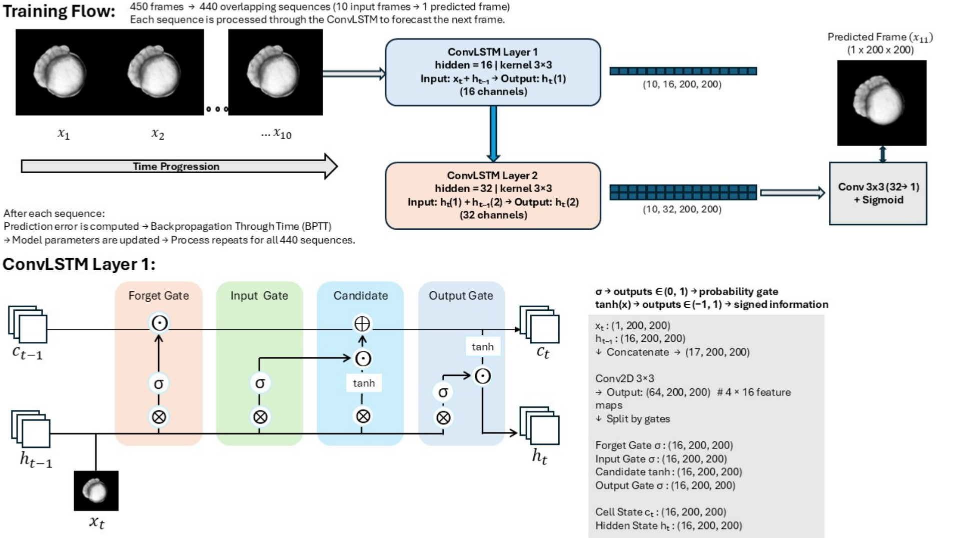
November 6, 2025

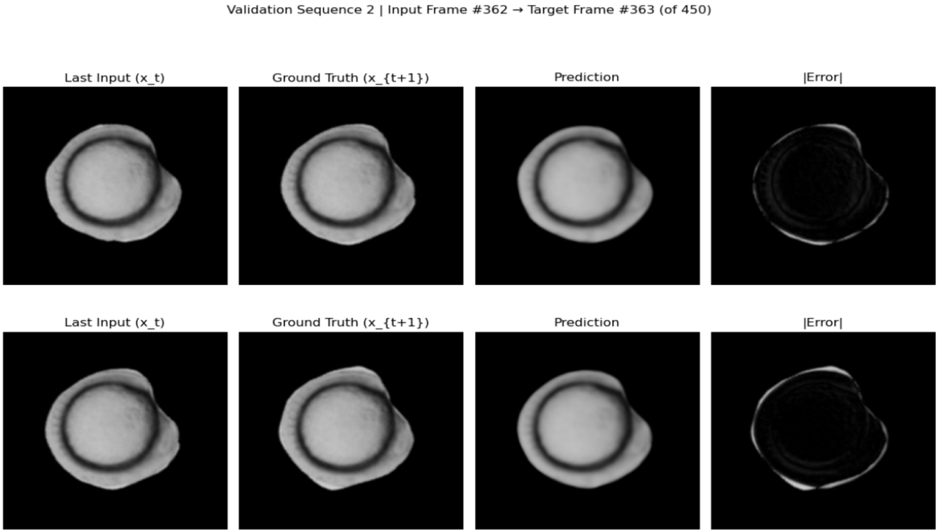
# Convolutional LSTM



# Pseudocode

```
# 1) Data -> Sequences
read_tiff_stacks()                                  # each: (450, 200, 200), grayscale
normalize_to_[0,1]()
TARGET = "Control1"

# Sliding window: past 10 -> predict next 1
(X, y) <- build_sequences(stack[TARGET], N_PAST=10, N_FUTURE=1)
split 80/20 -> (X_train, y_train), (X_val, y_val)
reshape:
  X_* -> (B, T=10, C=1, H=200, W=200)
  y_* -> (B, 1, 1, 200, 200)

# 2) Model (Forecaster)
ConvLSTM layer 1: input (1+16)=17 ch -> hidden=16, kernel 3×3 (same)
ConvLSTM layer 2: input (16+32)=48 ch -> hidden=32, kernel 3×3 (same)
Final Conv 3×3: 32 -> 1, then sigmoid
y' = model(X) uses last hidden state h_T to predict next frame

# 3) Loss = SSIM
loss_fn(y', y) = 1 − SSIM(y', y; data_range=1.0)

# 4) Training (BPTT)
for epoch in 1..E:
  for (Xb, yb) in train_loader:
    yb' = model(Xb)                 # processes T=10 time steps
    loss = 1 − SSIM(yb', yb)
    loss.backward(); optimizer.step()

  # Validation
  model.eval()
  val_loss = mean( 1 − SSIM(model(Xv), yv) over val_loader )
  print(epoch, train_loss_avg, val_loss)

# 5) Plotting
take one validation batch: (Xb, yb)
predict next frames: yb' = model(Xb)

  last_input   = Xb[i, t=last]            # last frame of the 10 inputs
  ground_truth = yb[i]                     # real next frame
  prediction   = yb'[i]                    # predicted next frame
  error_map    = |prediction − ground_truth|
```

# Results


Validation Sequence 2 | Input Frame #362 → Target Frame #363 (of 450)
Last Input (x_t)
Ground Truth (x_{t+1})
Prediction
|Error|
Last Input (x_t)
Ground Truth (x_{t+1})
Prediction
|Error|

```
Starting training...
Device: cuda
Epochs: 20
Epoch [01/20] - Time: 21.43s - Train Loss: 0.24090355 - Val Loss: 0.10868752
Epoch [02/20] - Time: 20.99s - Train Loss: 0.08105249 - Val Loss: 0.10245259
Epoch [03/20] - Time: 21.51s - Train Loss: 0.07899994 - Val Loss: 0.10324820
Epoch [04/20] - Time: 21.97s - Train Loss: 0.07917218 - Val Loss: 0.10193101
Epoch [05/20] - Time: 21.84s - Train Loss: 0.07819608 - Val Loss: 0.10136267
Epoch [06/20] - Time: 21.90s - Train Loss: 0.07835551 - Val Loss: 0.10211914
Epoch [07/20] - Time: 22.02s - Train Loss: 0.07790385 - Val Loss: 0.10195548
Epoch [08/20] - Time: 21.98s - Train Loss: 0.07736144 - Val Loss: 0.10197099
Epoch [09/20] - Time: 21.69s - Train Loss: 0.07743451 - Val Loss: 0.10166430
Epoch [10/20] - Time: 21.74s - Train Loss: 0.07702232 - Val Loss: 0.10078235
Epoch [11/20] - Time: 21.94s - Train Loss: 0.07698763 - Val Loss: 0.10151176
Epoch [12/20] - Time: 21.66s - Train Loss: 0.07662545 - Val Loss: 0.10044155
Epoch [13/20] - Time: 21.74s - Train Loss: 0.07643133 - Val Loss: 0.09992271
Epoch [14/20] - Time: 21.33s - Train Loss: 0.07613668 - Val Loss: 0.10021412
Epoch [15/20] - Time: 21.36s - Train Loss: 0.07623427 - Val Loss: 0.10264324
Epoch [16/20] - Time: 21.25s - Train Loss: 0.07631691 - Val Loss: 0.10134257
Epoch [17/20] - Time: 21.34s - Train Loss: 0.07572130 - Val Loss: 0.09936752
Epoch [18/20] - Time: 21.27s - Train Loss: 0.07580627 - Val Loss: 0.10166560
Epoch [19/20] - Time: 21.10s - Train Loss: 0.07589438 - Val Loss: 0.10023416
Epoch [20/20] - Time: 21.02s - Train Loss: 0.07573581 - Val Loss: 0.09998060
```