2023 GLOBAL SUMMIT ON ENVIRONMENTAL REMEDIATION

Long Term Ground Water Monitoring Using LSTM Algorithm for Anomaly Detection

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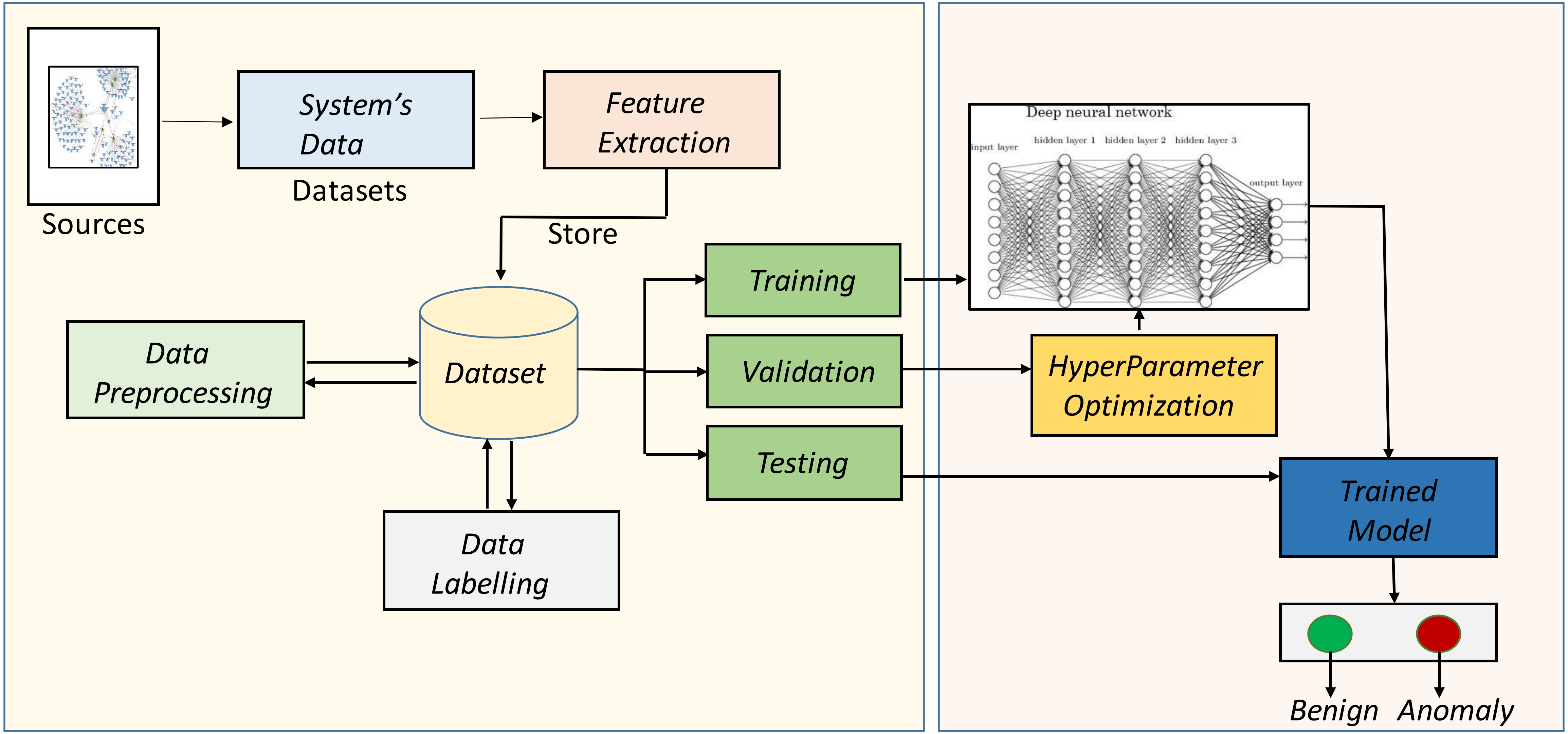
Significance

- Early detection can prevent long-term environmental damage.
- Ensures safe water quality for consumption and ecological balance.

Indicative of Larger Issues:

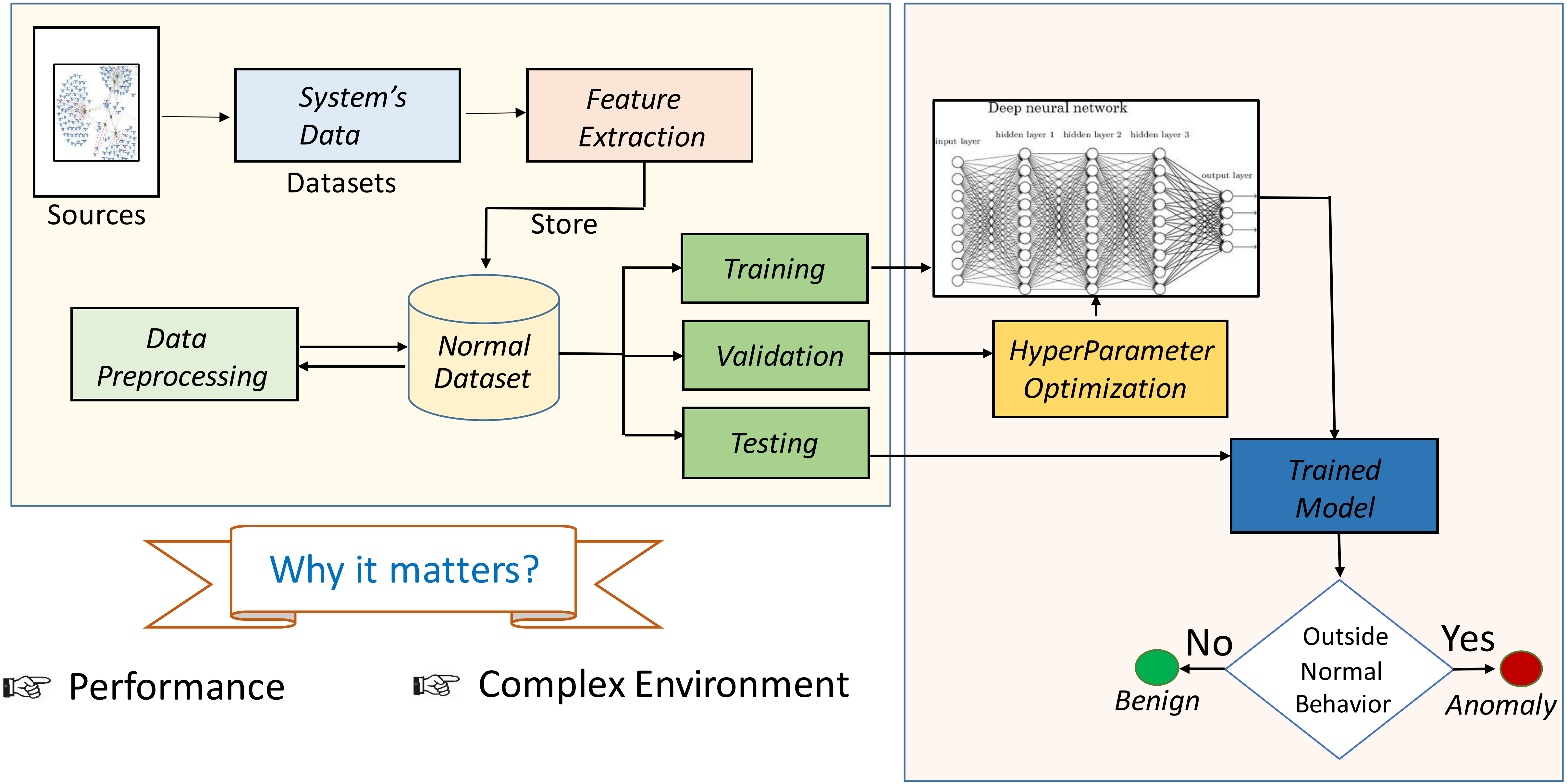
- Environmental: Contamination, infiltration of pollutants.
- Mechanical: Sensor malfunctions, equipment failures.

Conventional Way



☞ Needs Data Labelling ☞ Highly Imbalanced

Anomaly Detection



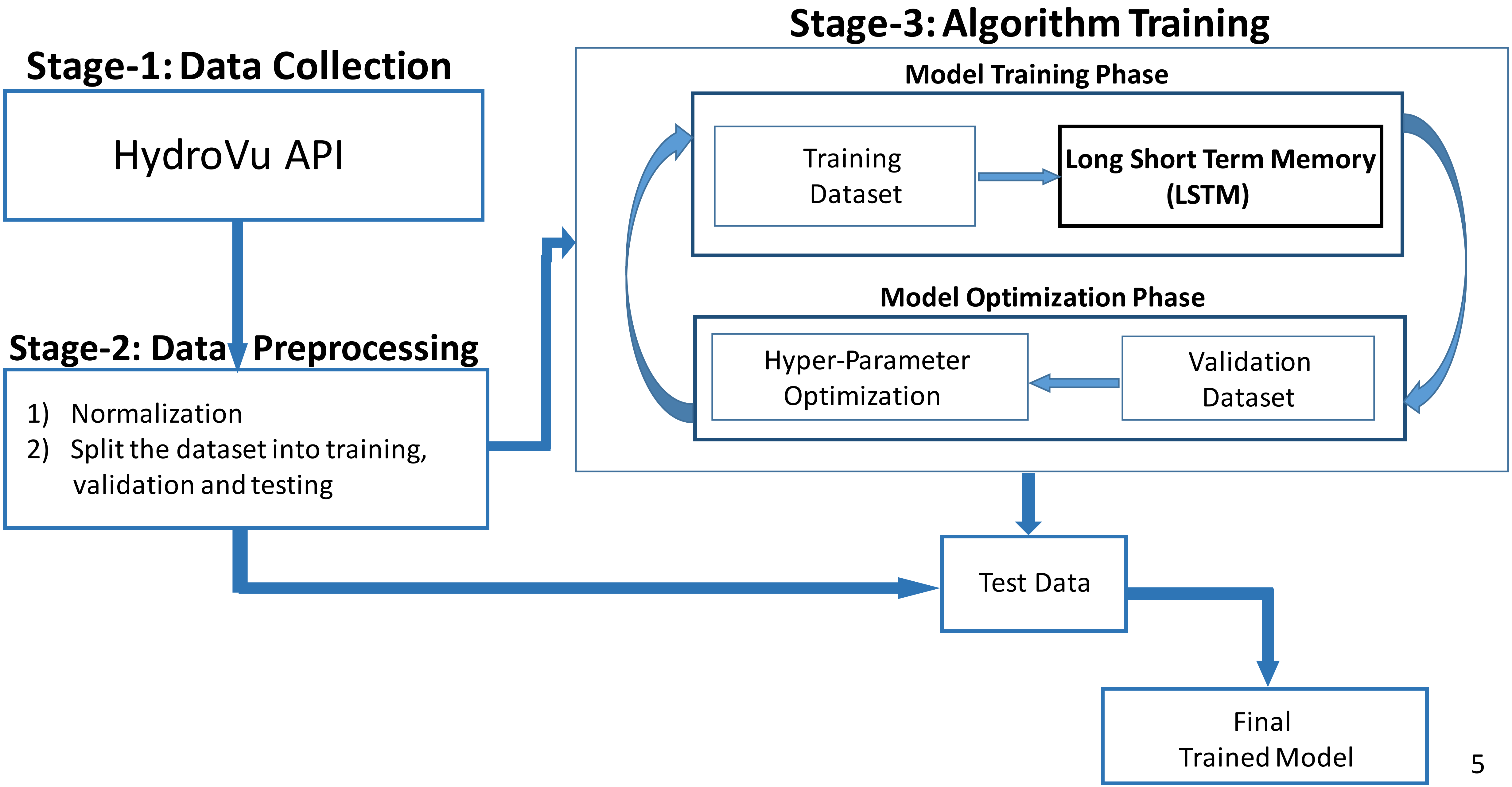
Why it matters?

- ☞ Performance
- ☞ Complex Environment

How to develop reliable AI-powered System?

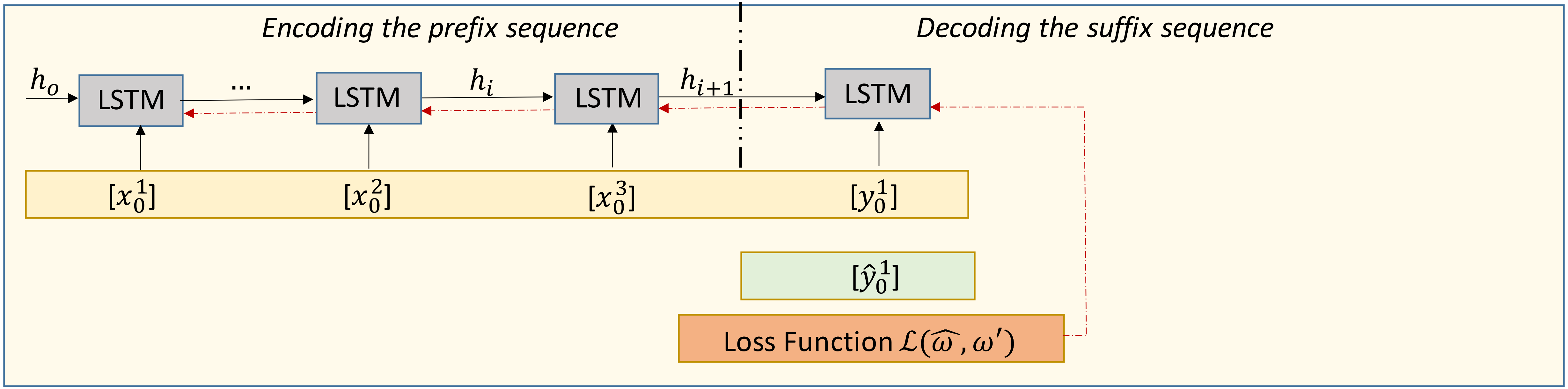
CHALLENGES

Applications	- How to reduce the training time of the deep learning algorithms?
Systems	- How to reduce the False Alarm Rate in a complex environment?
Theory	- How to build rigorous and robust deep learning model?


Stage-1: Data Collection
HydroVu API
Stage-2: Data Preprocessing
1) Normalization
2) Split the dataset into training, validation and testing
Stage-3: Algorithm Training
Model Training Phase
Training Dataset
Long Short Term Memory (LSTM)
Model Optimization Phase
Hyper-Parameter Optimization
Validation Dataset
Test Data
Final Trained Model

Sensor Dataset

StationId	DepthToWater
FSB116D	4161
FAI3B	3826
FAI11	3665
FAI8D	3568
FSB78	3445
FSB118D	3396
FSB127D	3158
FAI12	3150
FSB108D	3146
FEX4	3091



Batch Gradient Descent (BGD) | Mini-Batch Gradient Descent (MGD) | Stochastic Gradient Descent (SGD)

$$\theta = \theta - \eta . \nabla_\theta J(\theta)$$

$$\theta = \theta - \eta . \nabla_\theta J(\theta;\, x^{(i:i+n)};\, y^{(i:i+n)})$$

$$\theta = \theta - \eta . \nabla_\theta J(\theta;\, x^i;\, y^i)$$

☞ Underfitting

☞ Needs n before training

☞ Overfitting

Related Work

- Static Value
  - Fixed Value with no convergence guarantee
- Linear Scaling Rule
  - Straighforward Rule
- Gradual Scheme
  - Constraints: Tune at Epoch Level

Dy-BnLR Tuner:

- Hybrid BatchSize and LR
- Dynamic Tuning at runtime
- Temporal Weighted Correlations
- Apply to Different NNs

Dynamic BatchSize-LR Update Technique

Gradient Warmup | Loss Derivation | Weighted Loss | Update BatchSize

Dynamic BatchSize-LR Update Technique

Gradient Warmup

Loss Derivation

Weighted Loss

Update BatchSize

$$B = \sqrt{N}$$

Dynamic BatchSize-LR Update Technique

Gradient Warmup

Loss Derivation

Weighted Loss

Update BatchSize

$$B = \sqrt{N}$$

$$\mathcal{L}(\theta) = \frac{1}{B}\sum_{i=0}^{B-1}\mathcal{L}(X[i],\theta)$$

$$\theta^{k+1} = \theta^{k} - \eta\frac{1}{B}\sum_{i=0}^{B-1}\nabla\mathcal{L}(X[i],\theta)$$

Dynamic BatchSize-LR Update Technique

Gradient Warmup

Loss Derivation

Weighted Loss

Update BatchSize

$$B = \sqrt{N}$$

$$\mathcal{L}(\theta) = \frac{1}{B}\sum_{i=0}^{B-1} \mathcal{L}(X[i], \theta)$$

$$\theta^{k+1} = \theta^{k} - \eta \frac{1}{B}\sum_{i=0}^{B-1} \nabla\mathcal{L}(X[i], \theta)$$

$$\Delta BS = \sum_{k=i-1}^{0} (Normalized_{BS} * Weight_i)$$

$$\frac{\mathcal{L}_{BS_k} - \mathcal{L}_{BS_{k+1}}}{max\left(\left|\mathcal{L}_{BS_k}\right|, \left|\mathcal{L}_{BS_{k+1}}\right|\right)} * \frac{1}{2^{i-k}}$$

$$\Delta BS = \frac{\mathcal{L}_{BS_{i-1}} - \mathcal{L}_{BS_i}}{max\left(\left|\mathcal{L}_{BS_{i-1}}\right|, \left|\mathcal{L}_{BS_i}\right|\right)} * w_i + \frac{\mathcal{L}_{BS_{i-2}} - \mathcal{L}_{BS_{i-1}}}{max\left(\left|\mathcal{L}_{BS_{i-2}}\right|, \left|\mathcal{L}_{BS_{i-1}}\right|\right)} * w_{i-1} + \ldots\ldots + \frac{\mathcal{L}_{BS_1} - \mathcal{L}_{BS_2}}{max\left(\left|\mathcal{L}_{BS_1}\right|, \left|\mathcal{L}_{BS_2}\right|\right)} * w_1$$

Dynamic BatchSize-LR Update Technique

Gradient Warmup

$$B = \sqrt{N}$$

Loss Derivation

$$\mathcal{L}(\theta) = \frac{1}{B}\sum_{i=0}^{B-1}\mathcal{L}(X[i],\theta)$$

$$\theta^{k+1} = \theta^{k} - \eta\frac{1}{B}\sum_{i=0}^{B-1}\nabla\mathcal{L}(X[i],\theta)$$

Weighted Loss

$$\Delta BS = \sum_{k=i-1}^{0}(Normalized_{BS} * Weight_i)$$

$$\frac{\mathcal{L}_{BS_k} - \mathcal{L}_{BS_{k+1}}}{max\left(\left|\mathcal{L}_{BS_k}\right|,\left|\mathcal{L}_{BS_{k+1}}\right|\right)} * \frac{1}{2^{i-k}}$$

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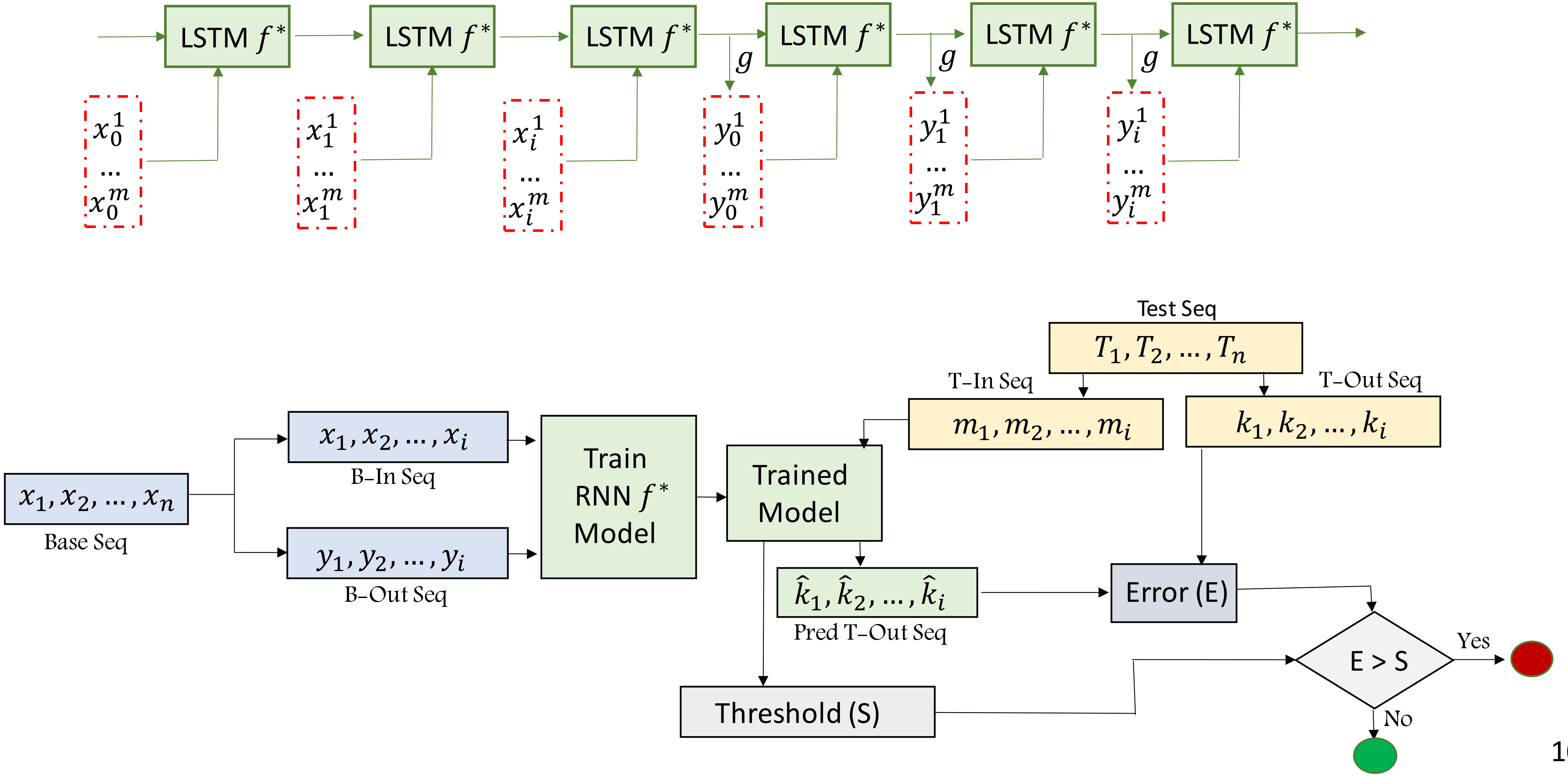
Update BatchSize

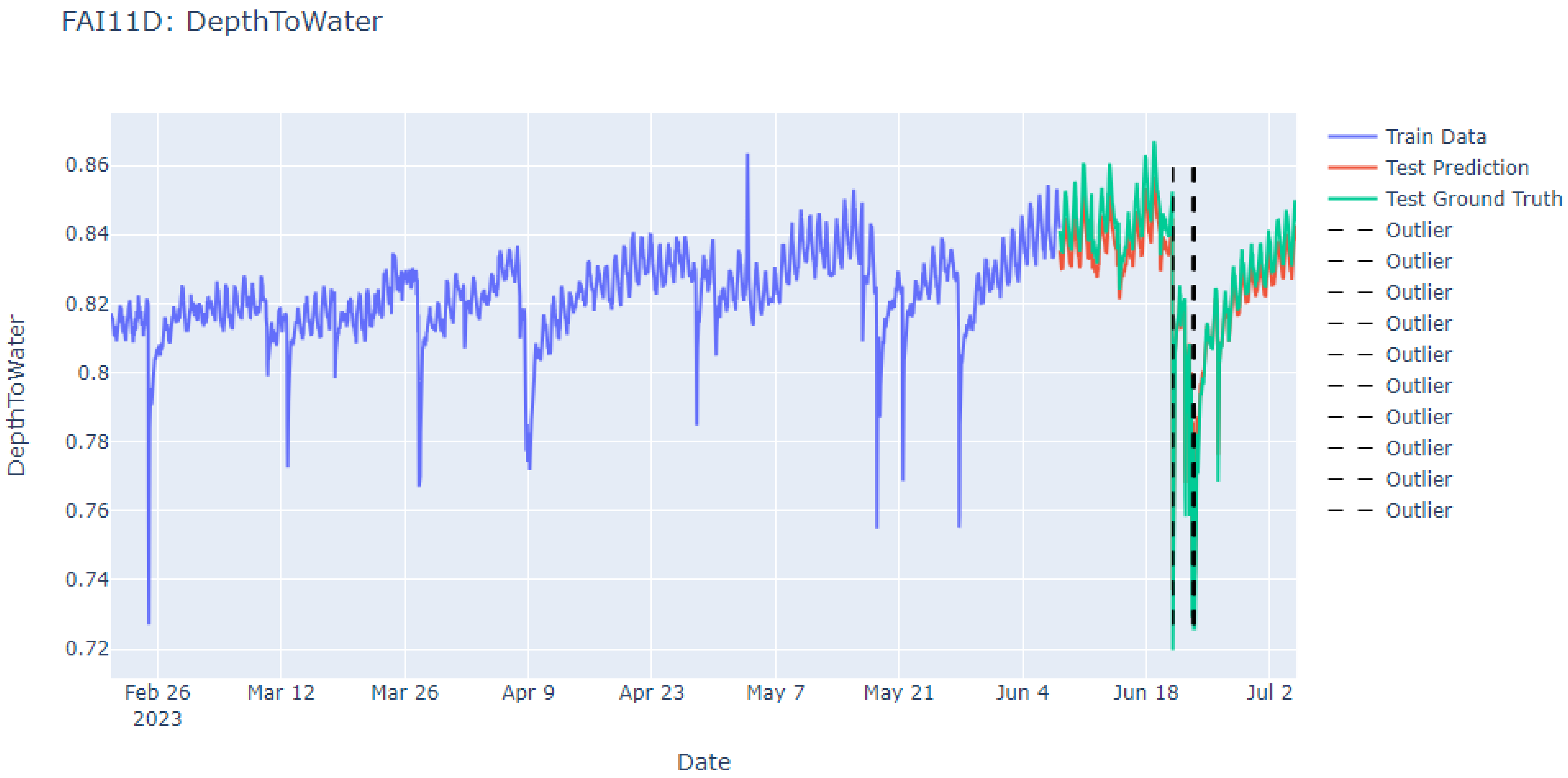
$$BS_{i+1} = BS_i * (1 + \Delta BS)$$

Epoch 1	Epoch 2	Epoch 3	Epoch 4	
BatchSize	LR	BatchSize	LR	.....

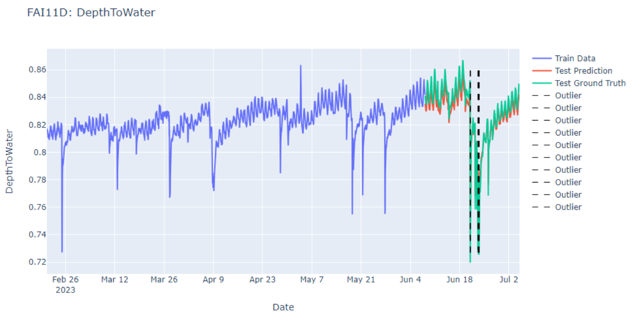
Anomaly Detection



Results


FAI11D: DepthToWater
DepthToWater
0.86
0.84
0.82
0.8
0.78
0.76
0.74
0.72
Feb 26
2023
Mar 12
Mar 26
Apr 9
Apr 23
May 7
May 21
Jun 4
Jun 18
Jul 2
Date
Train Data
Test Prediction
Test Ground Truth
Outlier
Outlier
Outlier
Outlier
Outlier
Outlier
Outlier
Outlier
Outlier
Outlier

Results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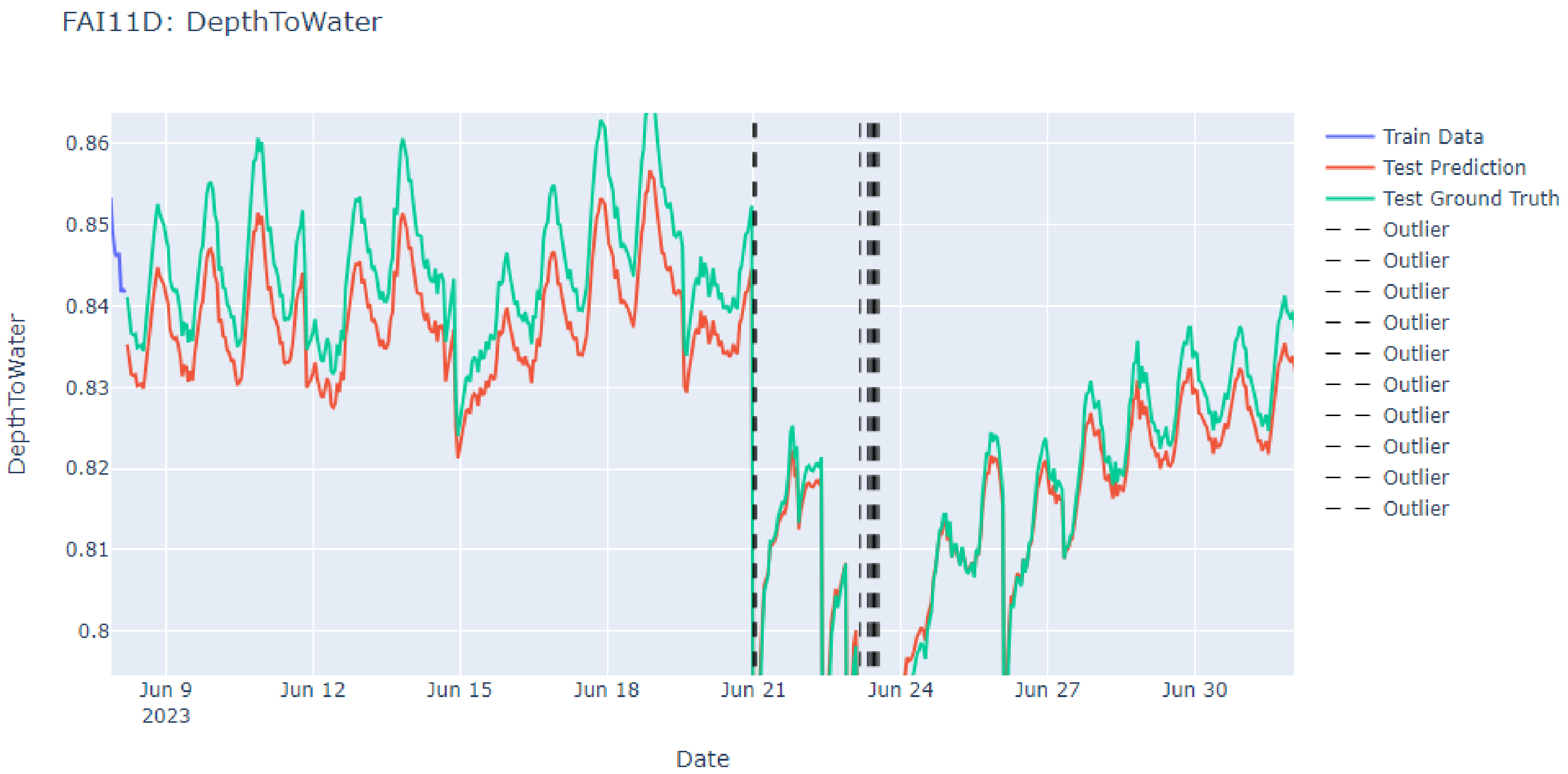
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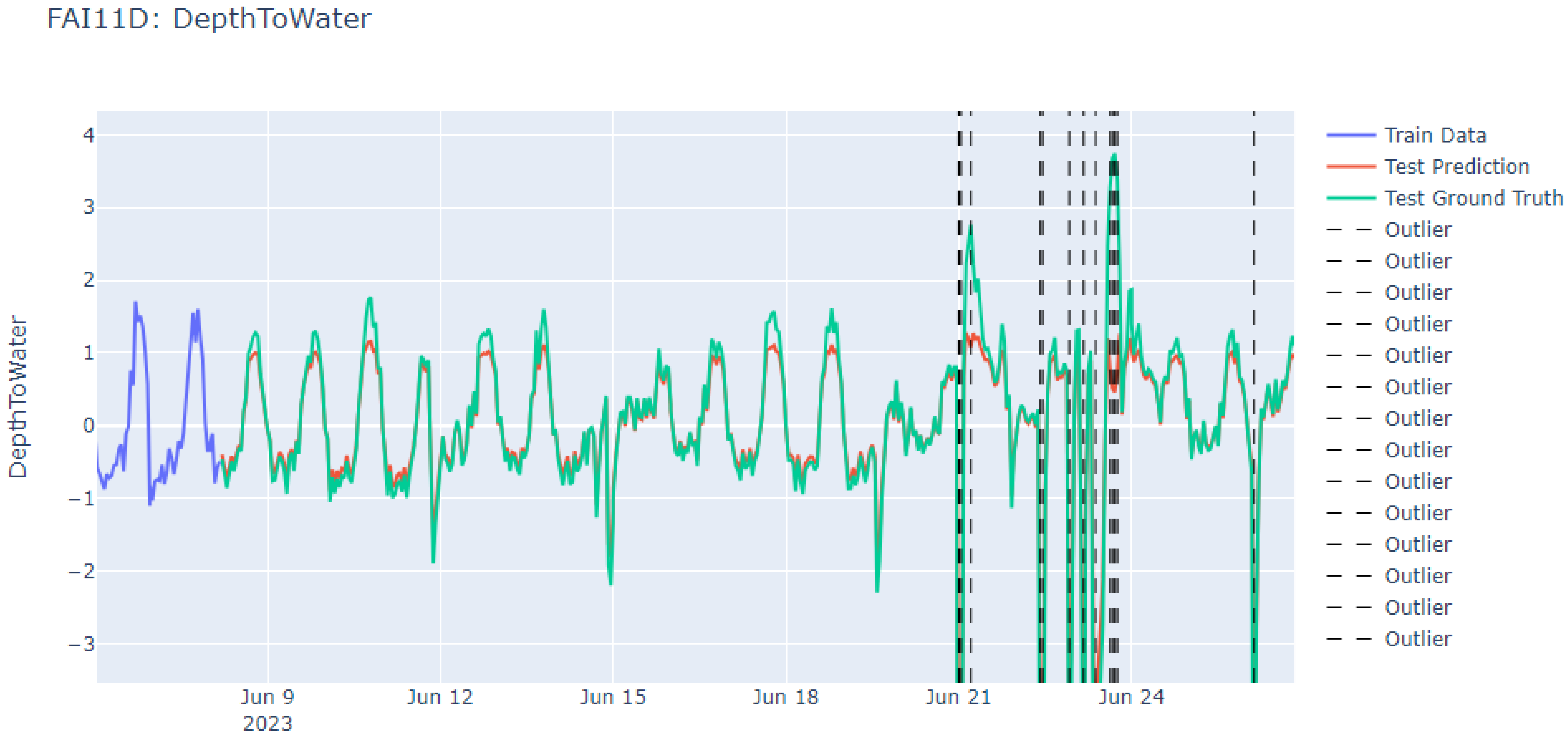
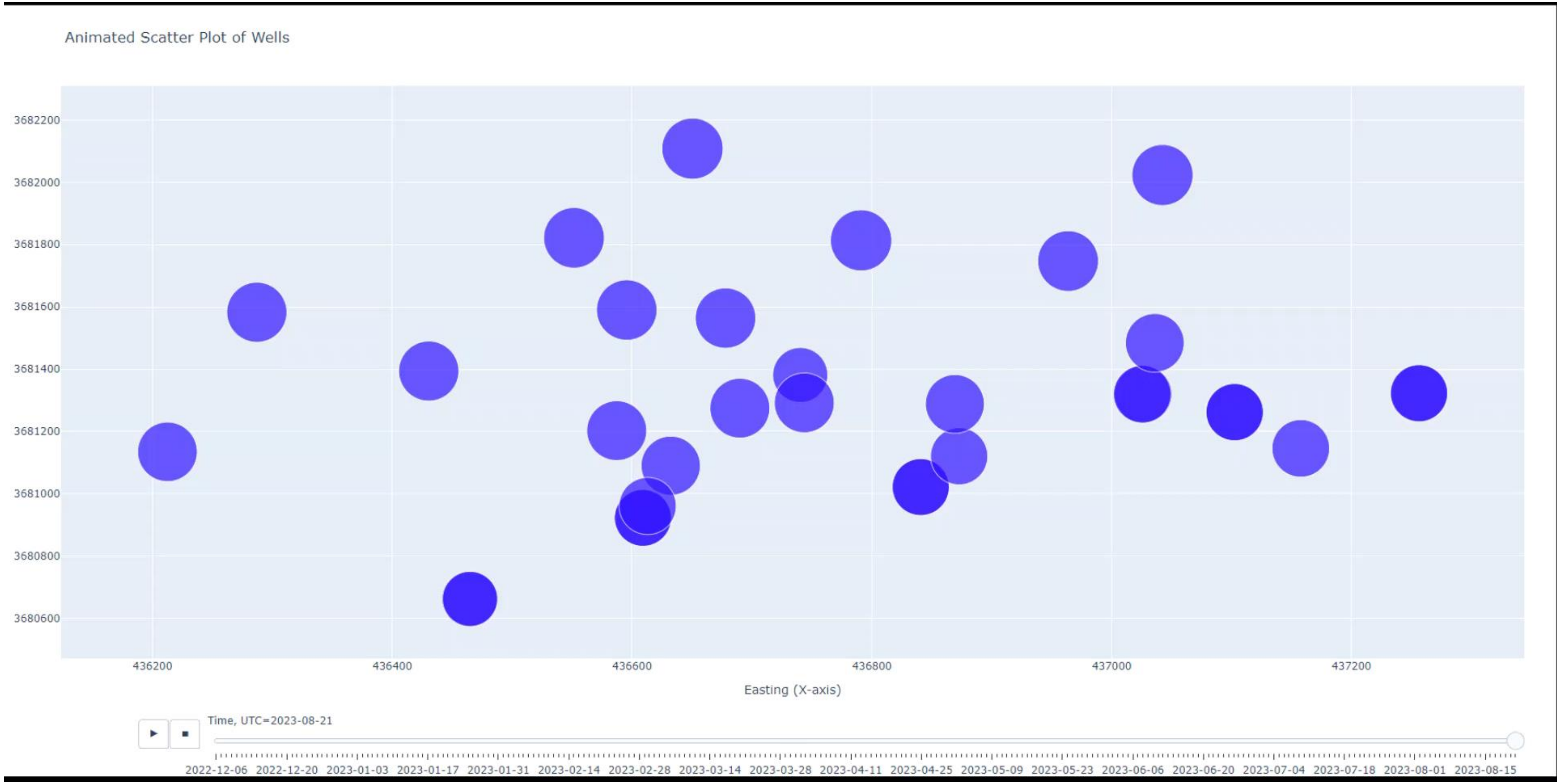
Results



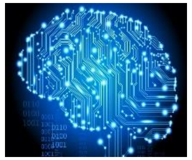
Smoothing Technique: Noise reduction noise and filter out high-frequency fluctuations.
Differencing method: Eliminate daily fluctuations or seasonality patterns.
Normalization: To ensure consistency.

Anomaly Detection Animation

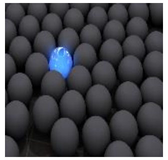


Explainable & Verifiable AI

Rigorous and robust AI



Deep Learning



AD

- How to improve DL explainability?
  Feature Space, intermediate process

- How to verify and support online learning?

Thank You

Questions ?

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