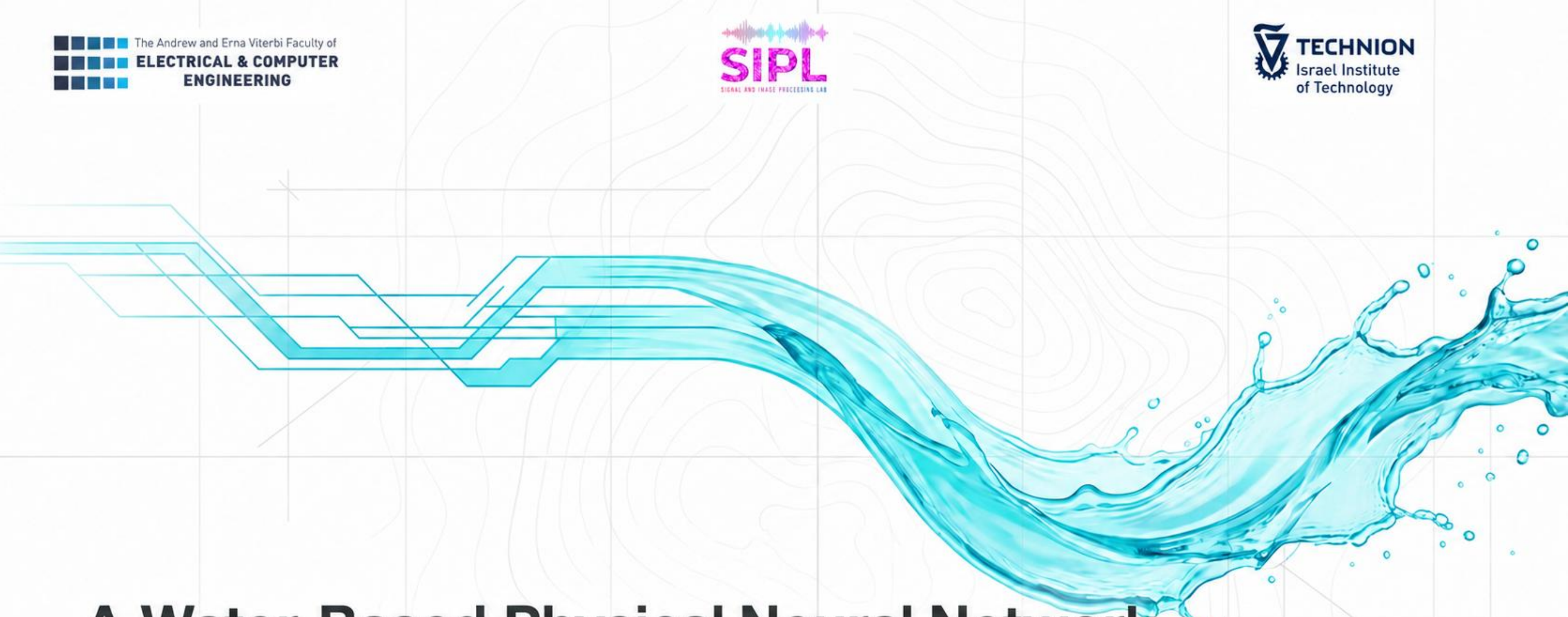




# A Water-Based Physical Neural Network

**Presenters:** Matan Babash & Alon Elhayani

**Supervisors:** Hila Manor & Noa Cohen

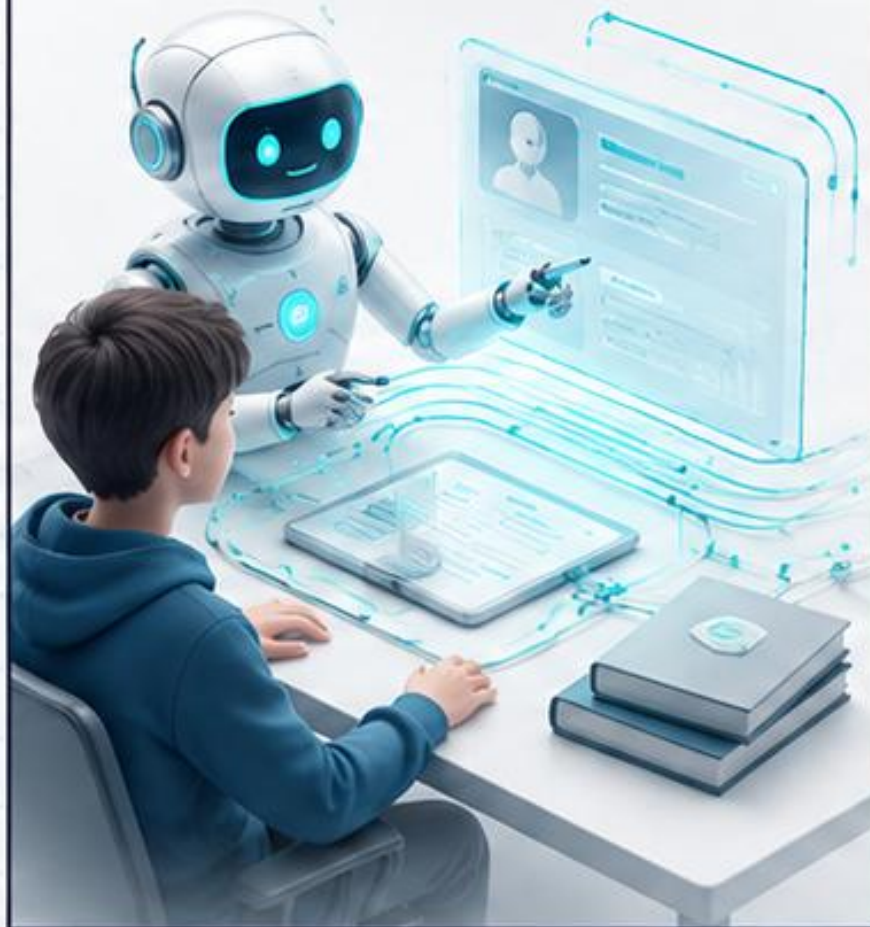
**Date:** 26.05.2026

# AI Changes the World

**Software Development:**  
Smarter coding and automation.



**Education:**  
AI as a teacher and personalized learning source.



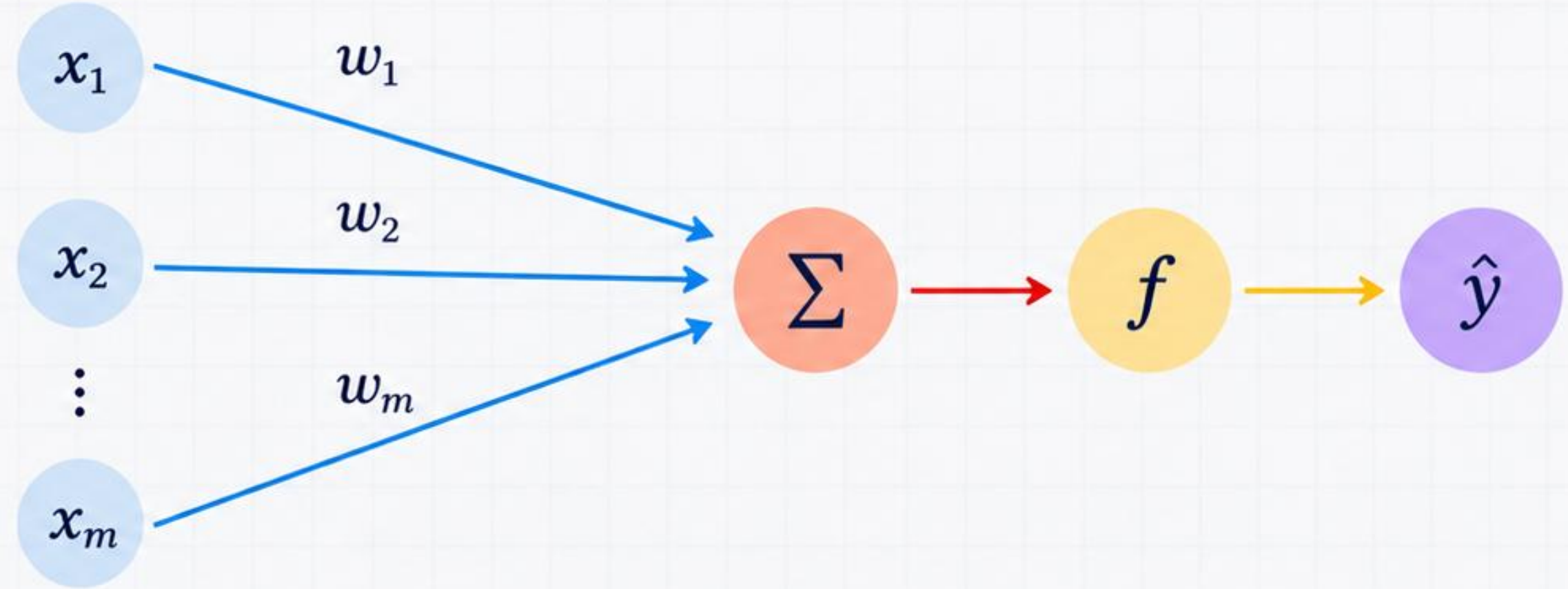
**Content Creation:**  
Generating ideas, writing, and designing.



**Media & Entertainment:**  
Creating engaging content and experiences.



# The Single Neuron



Inputs



$x_1, x_2, \dots, x_m$

Weights



$w_1, w_2, \dots, w_m$

Sum



$$z = \sum_{i=1}^m w_i x_i$$

Non-Linearity



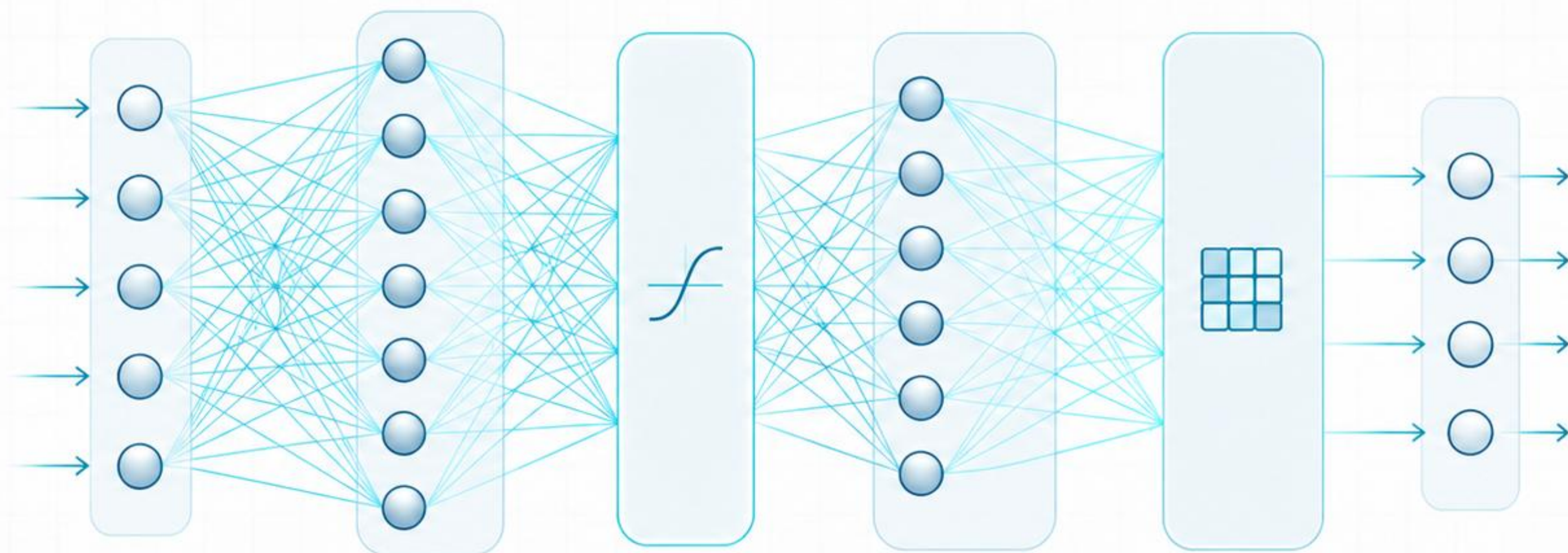
$f(z)$

Output

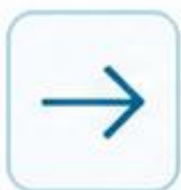


$\hat{y} = f(z)$

# The Neural Network



Inputs



Neurons  
(Dense Layer)



Activation  
Layer



Neurons  
(Dense Layer)



Pooling  
Layer

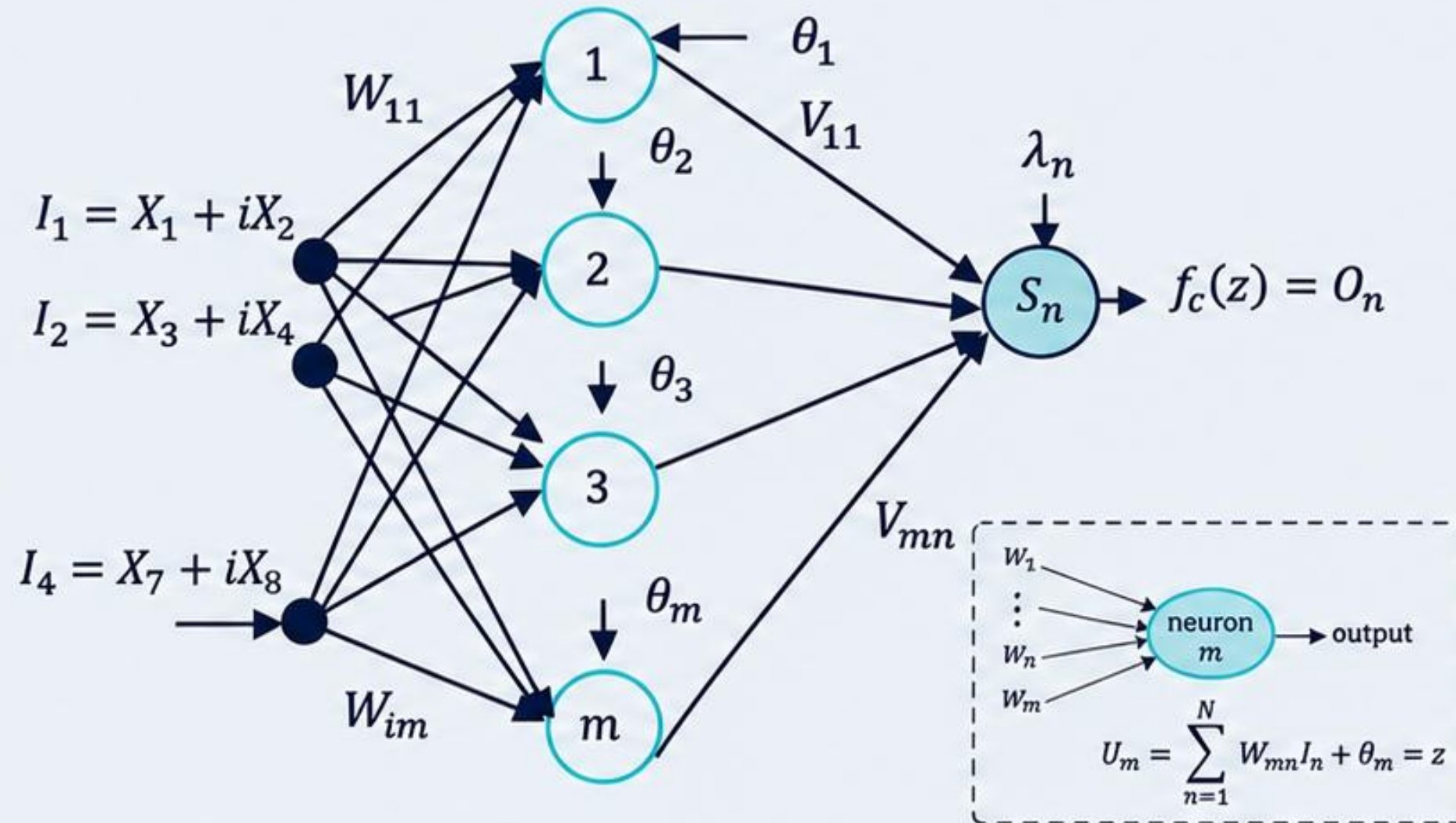


Outputs

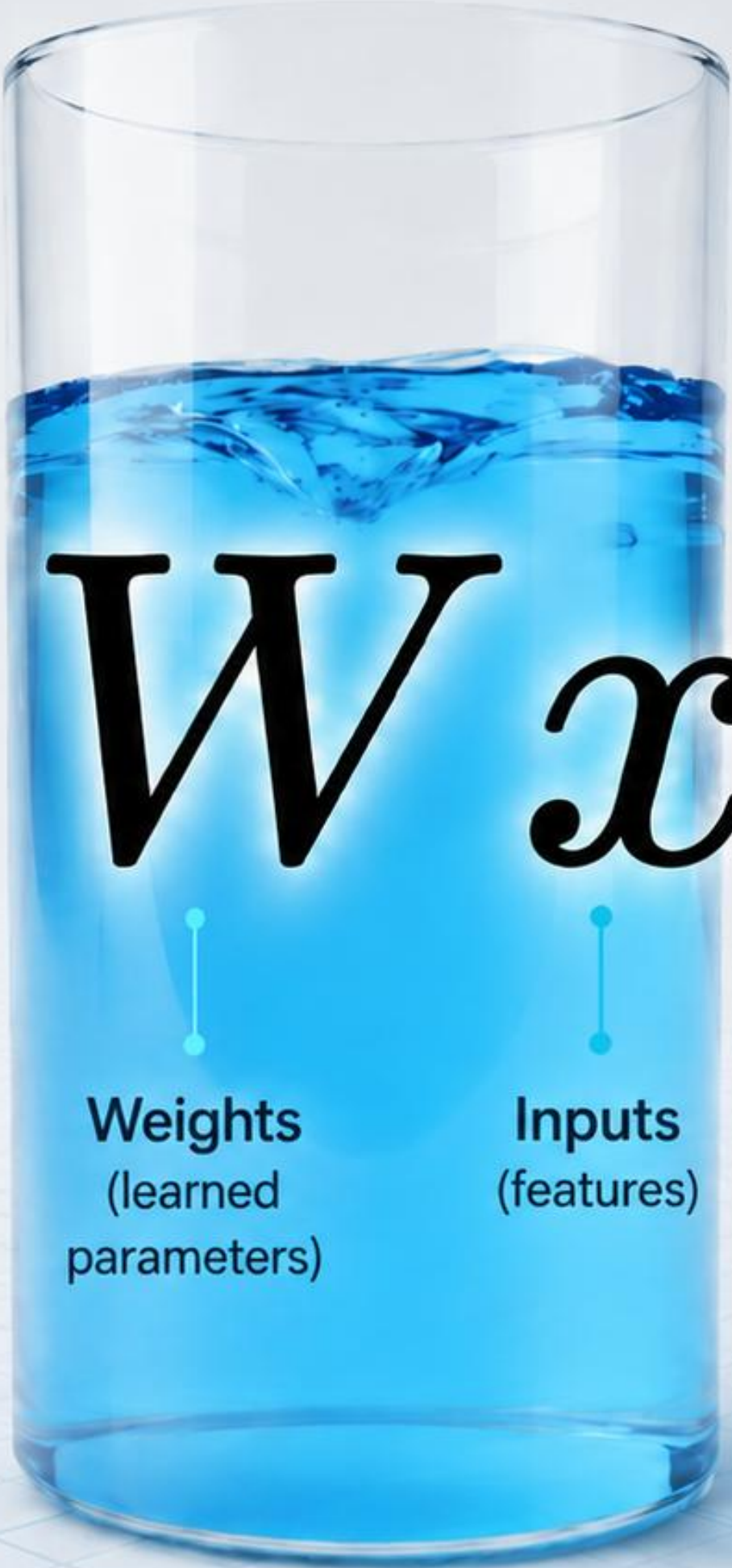


# The Abstraction Barrier in Machine Learning Education

## The Mathematical Reality



**The Gap:** We rely on highly abstract mathematics to explain systems that make highly tangible decisions. How do we make the invisible visible?



The diagram illustrates the linear equation  $y = wx + b$  using a glass of blue liquid as a metaphor. The glass is filled with blue liquid, and the equation is superimposed on it. The liquid level represents the output  $y$ . The weight  $w$  and input  $x$  are represented by the liquid level, with  $w$  being the learned parameters and  $x$  being the features. The bias  $b$  is represented by the offset from the origin.

$$y = wx + b$$

**Output**  
(prediction)

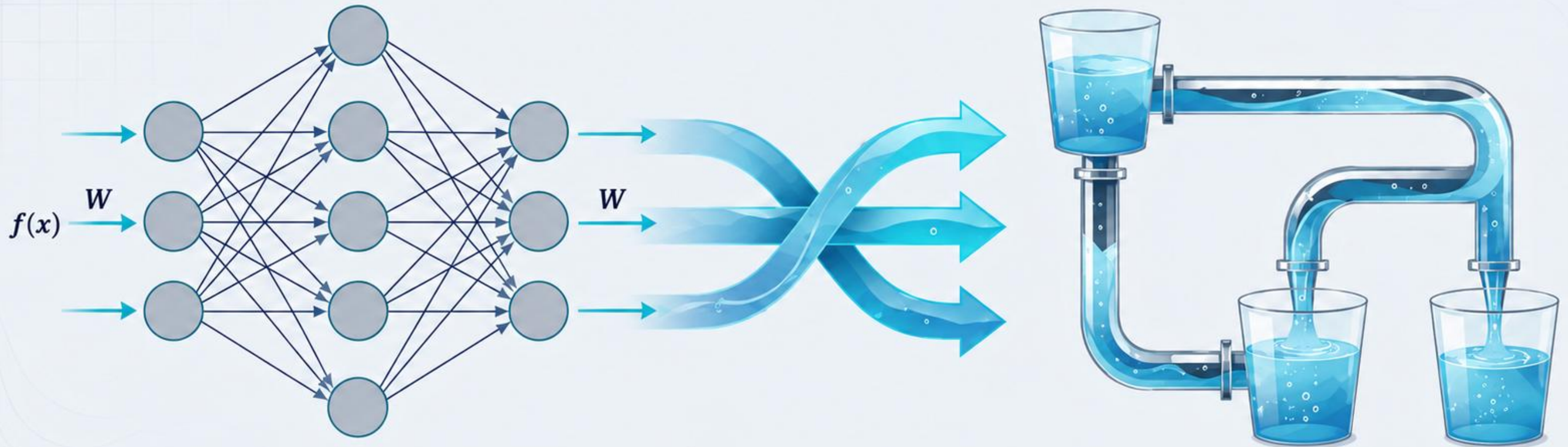
**Weights**  
(learned parameters)

**Inputs**  
(features)

**Bias**  
(offset)

# Bridging Intuition and Mathematics

What if we can use water instead?



# Making the Invisible Visible

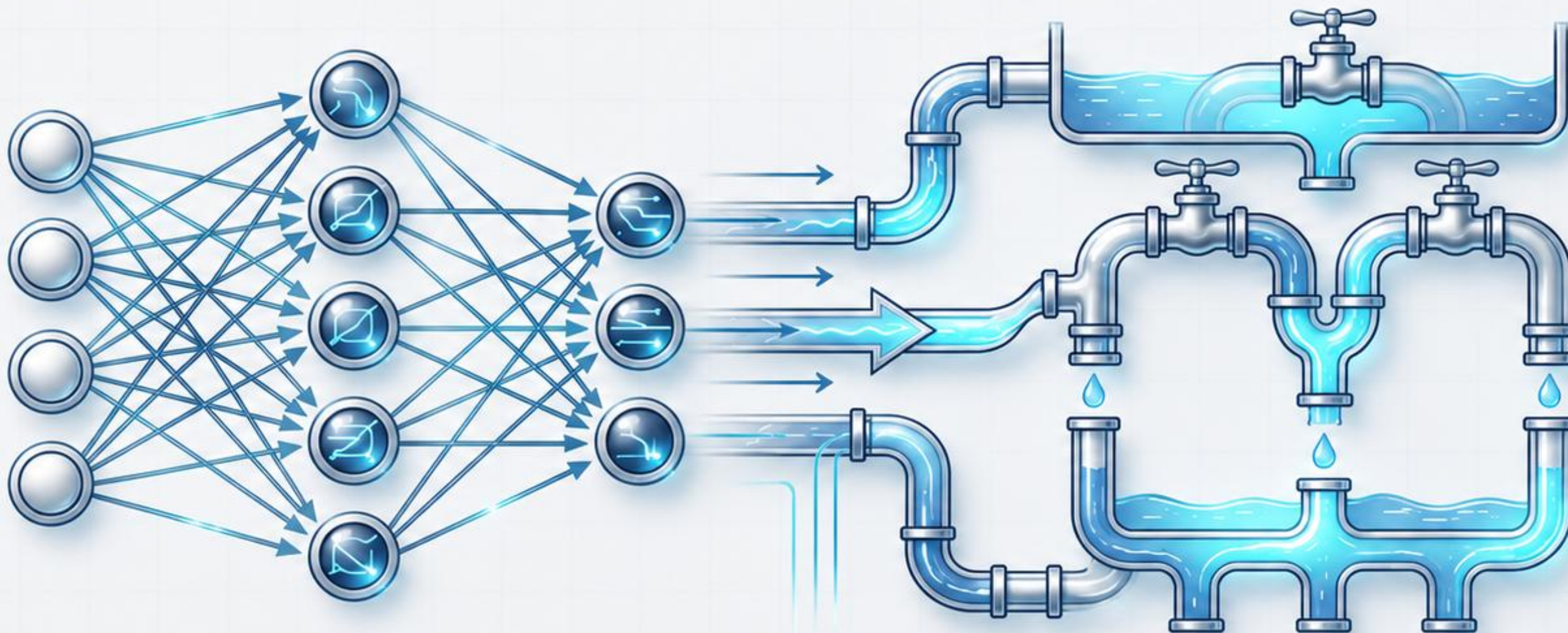
**The Idea:** Build a physical model to illustrate network mechanics.

## The Translation:

- Neuron = Container
- Weights = Volume
- Moving Data = Water Flow

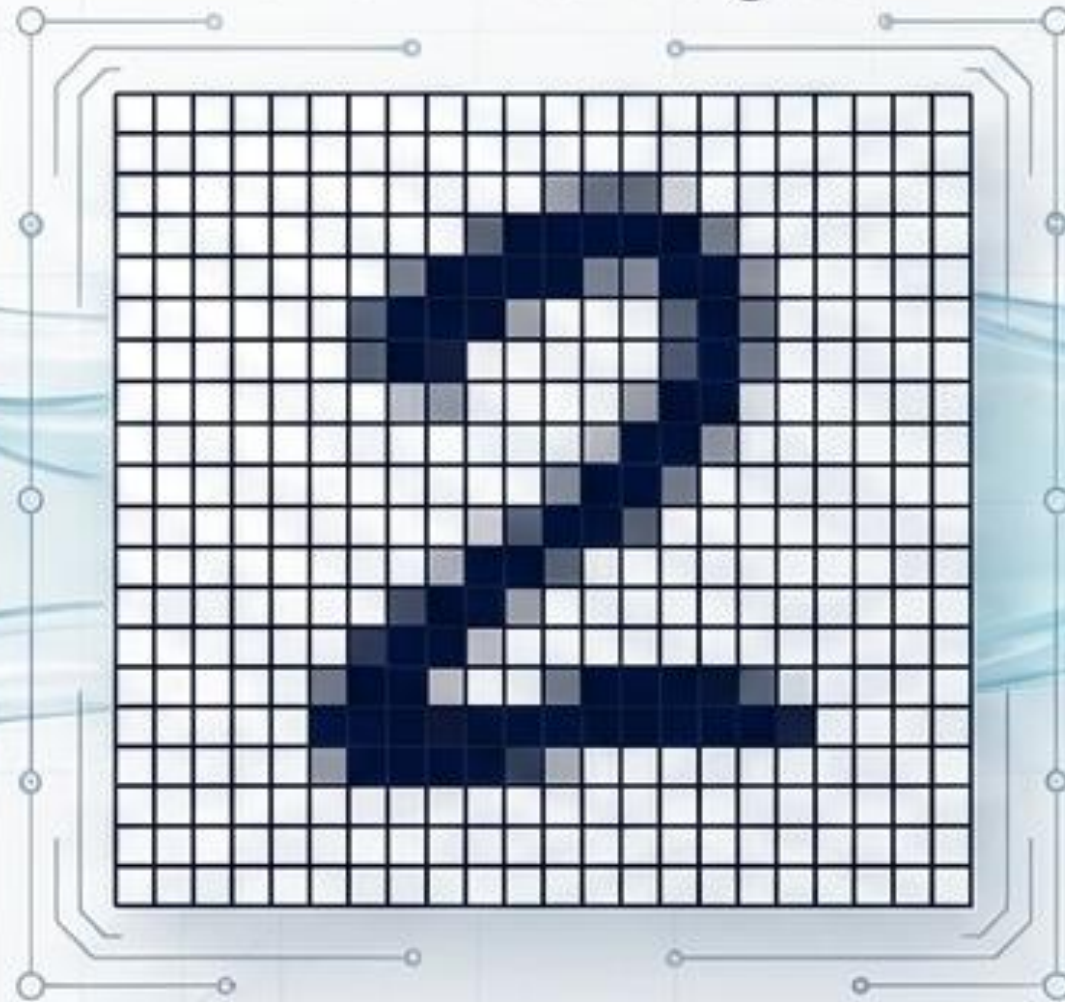
## Goals:

- Educational: Simplify machine learning principles.
- Conceptual: Implement mechanics over digital computation.



# Distilling the MNIST Dataset

**Original:** 28x28  
handwritten digits



**Original:** 28x28  
handwritten digits

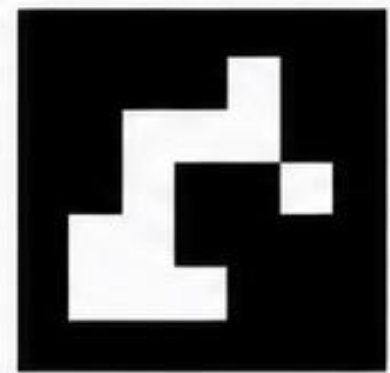
**Preprocessing:**  
Thresholding and refinement

**Output:** 8x8 input grid  
for physical training

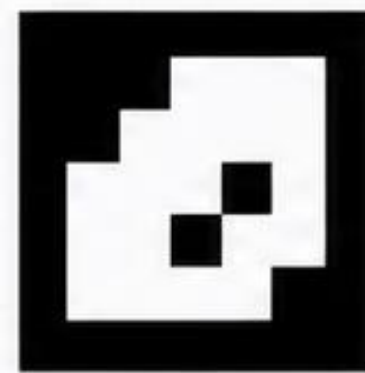


**Output:** 8x8 input grid  
for physical training

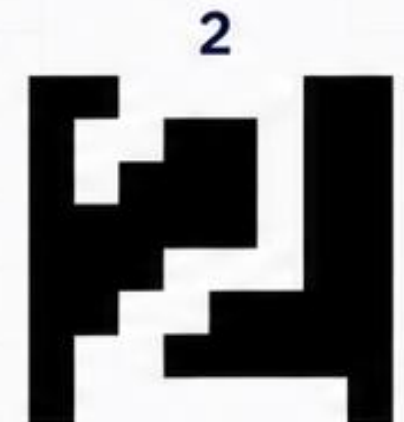
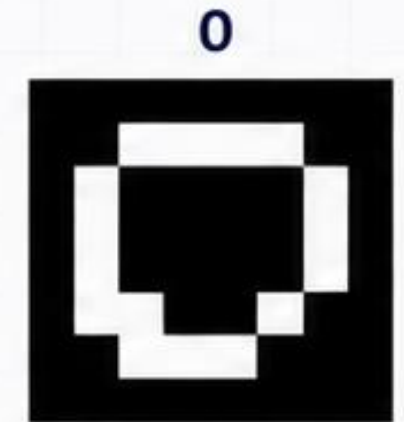
# Data Refinement Pipeline



Choosing  
The Right  
Threshold



Manual  
Refinements

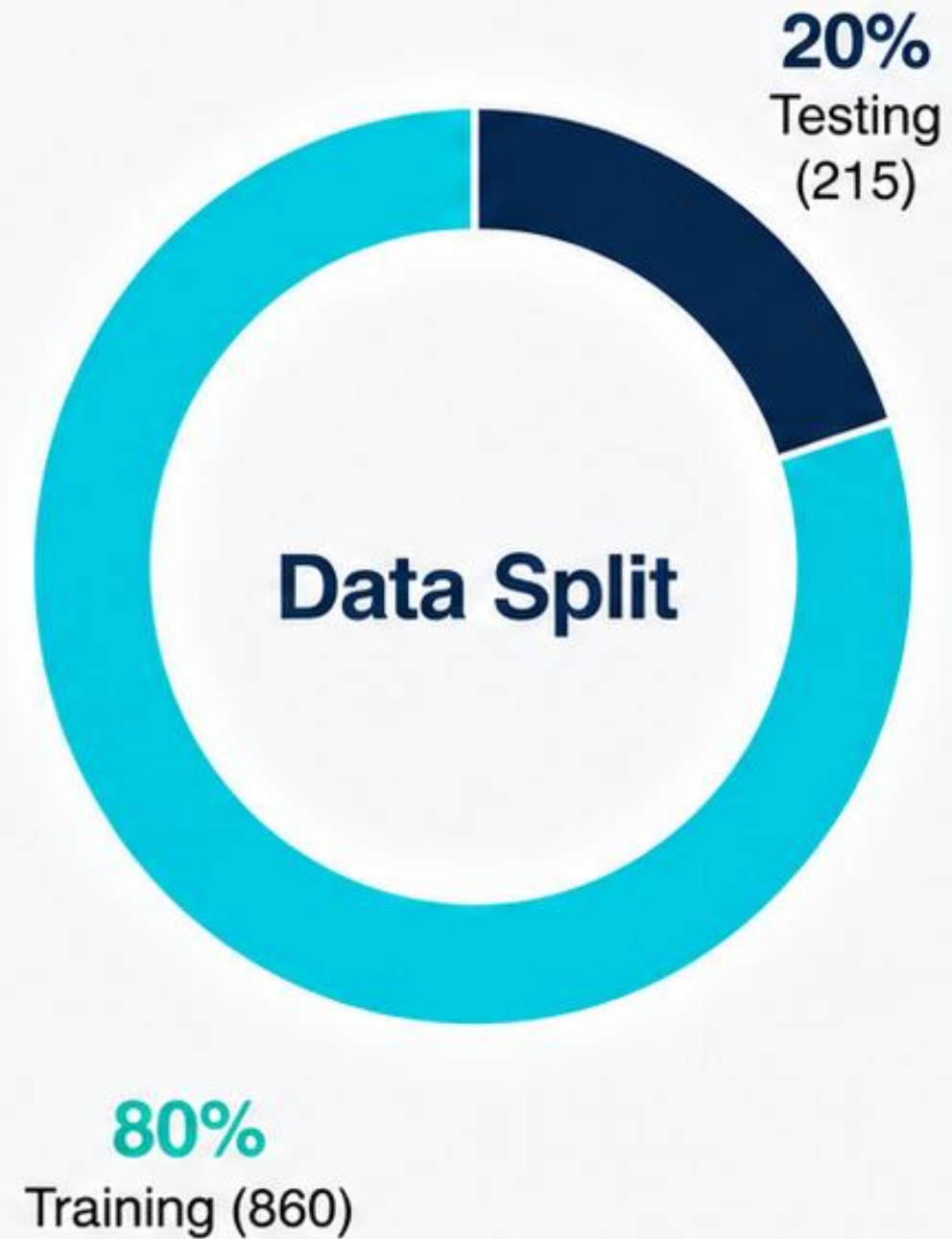


# Dataset Composition & Augmentation

**1,075**

**Total Curated  
Images**

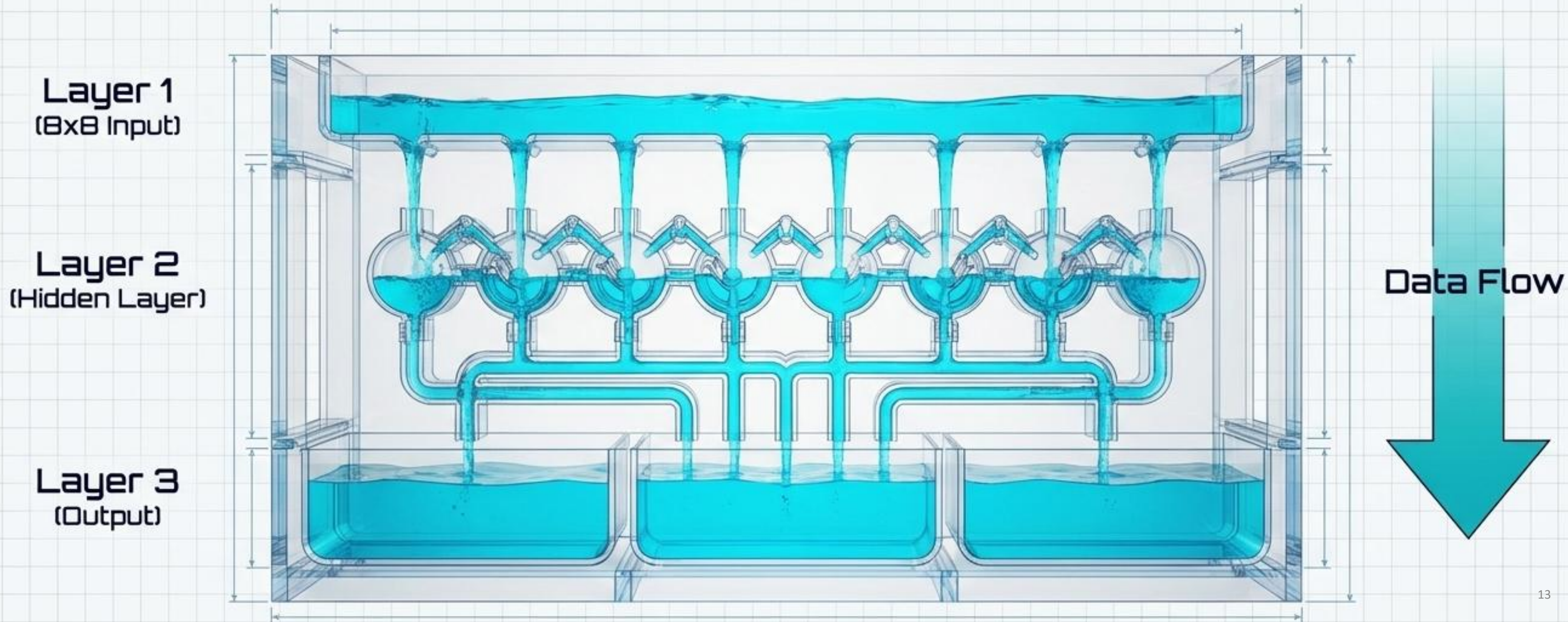
Highly ambiguous or poorly drawn samples were manually filtered to prevent physical miscalibration.



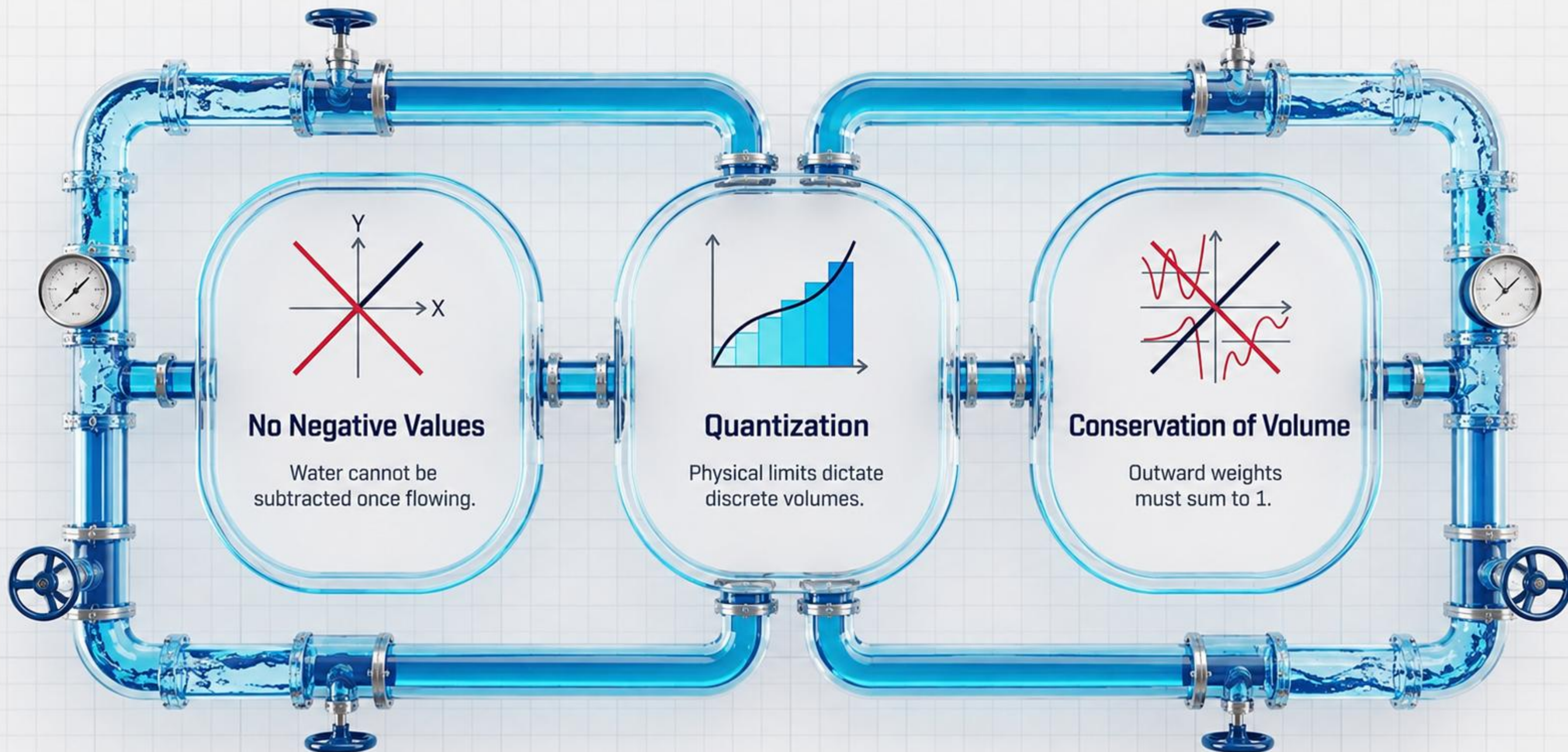
# Utilizing Gravity as the Processor

**The Problem:** Data must move simultaneously.

**The Physics Solution:** Rotate the network 90 degrees downward.



# Constraint Framework



# Physical Constraints as Optimization Problem

---

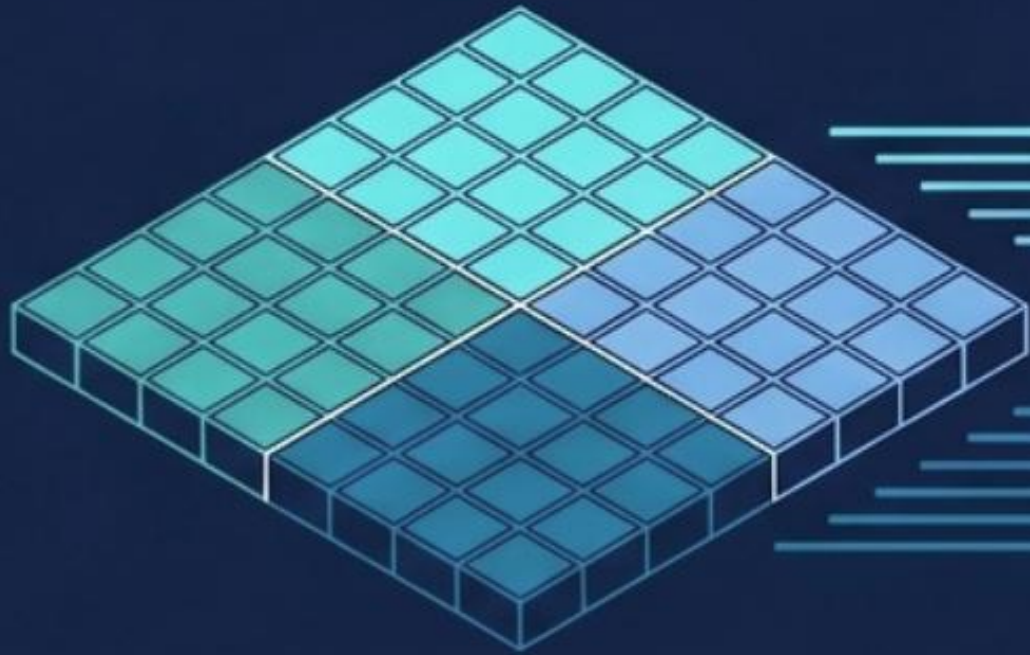
$$\begin{array}{ll} \min_W & \mathcal{L}(W) \quad (\text{classification loss}) \\ \text{such that} & \left\{ \begin{array}{ll} 0 \leq W_{ij} \leq 1 & (\text{non-negative physical flow}) \\ W_{ij} \in \mathcal{Q} & (\text{quantized, realizable values}) \\ \sum_j W_{ij} = 1, \forall i & (\text{conservation of volume}) \end{array} \right. \end{array}$$

**Weights must satisfy physically realizable flow constraints:**

non-negative, quantized (2 decimal places), and sum to exactly 1 for each hidden neuron.

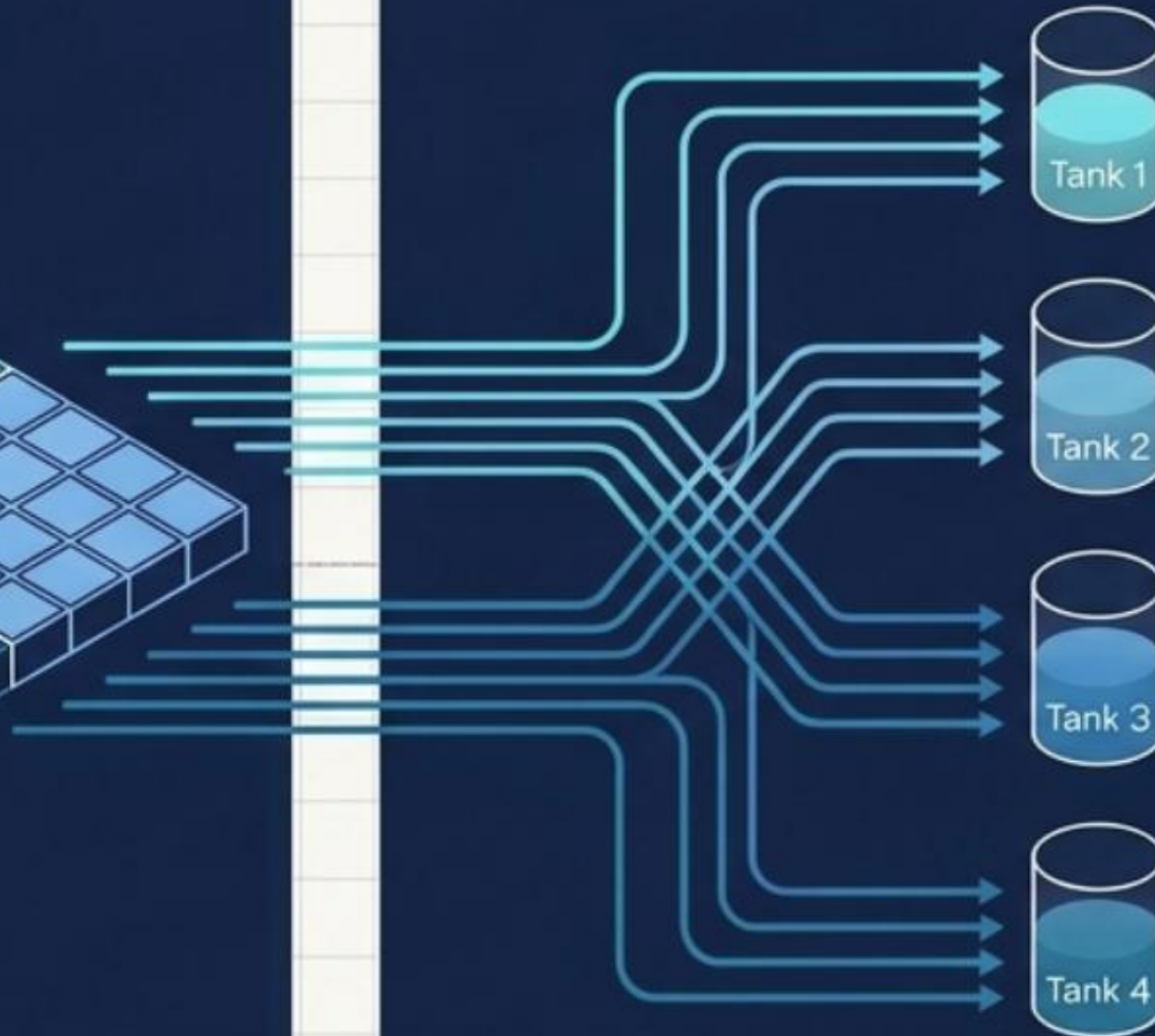
# The Architecture: Localized Processing

Input Layer (64 Nodes)



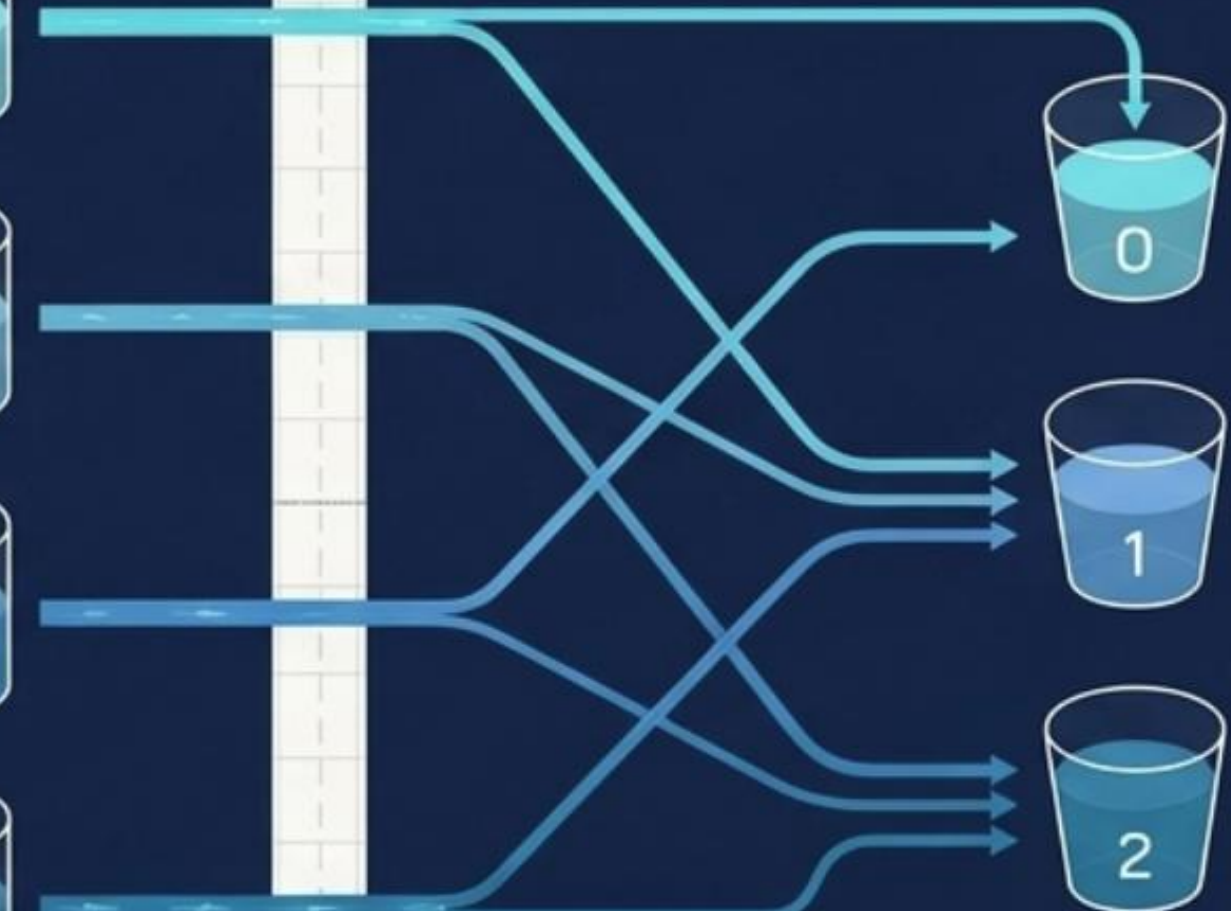
The compressed 8x8 MNIST digit is split into four distinct 4x4 spatial regions.

Hidden Layer (4 Nodes)



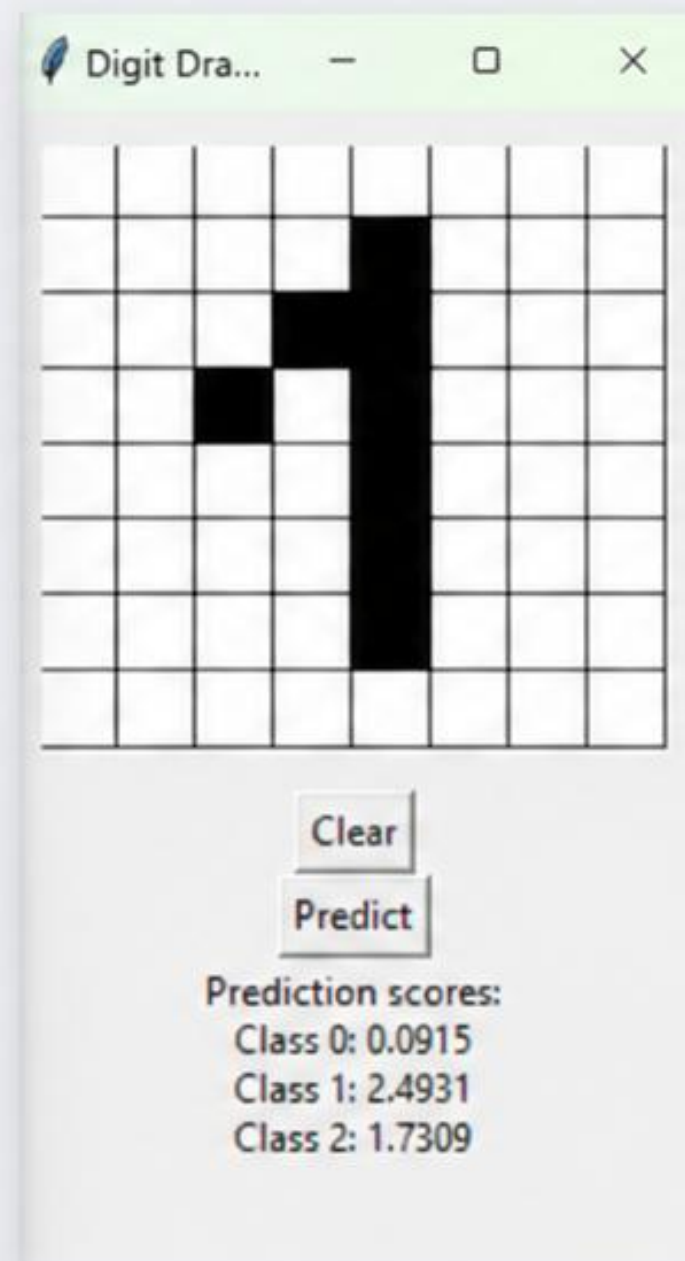
Each quadrant feeds exclusively into its own dedicated hidden neuron, drastically reducing physical complexity and tube crossing.

Output Layer (3 Nodes)



The four hidden neurons distribute their accumulated fluid into three output buckets representing the final classifications.

# Simulation for Confidence Level

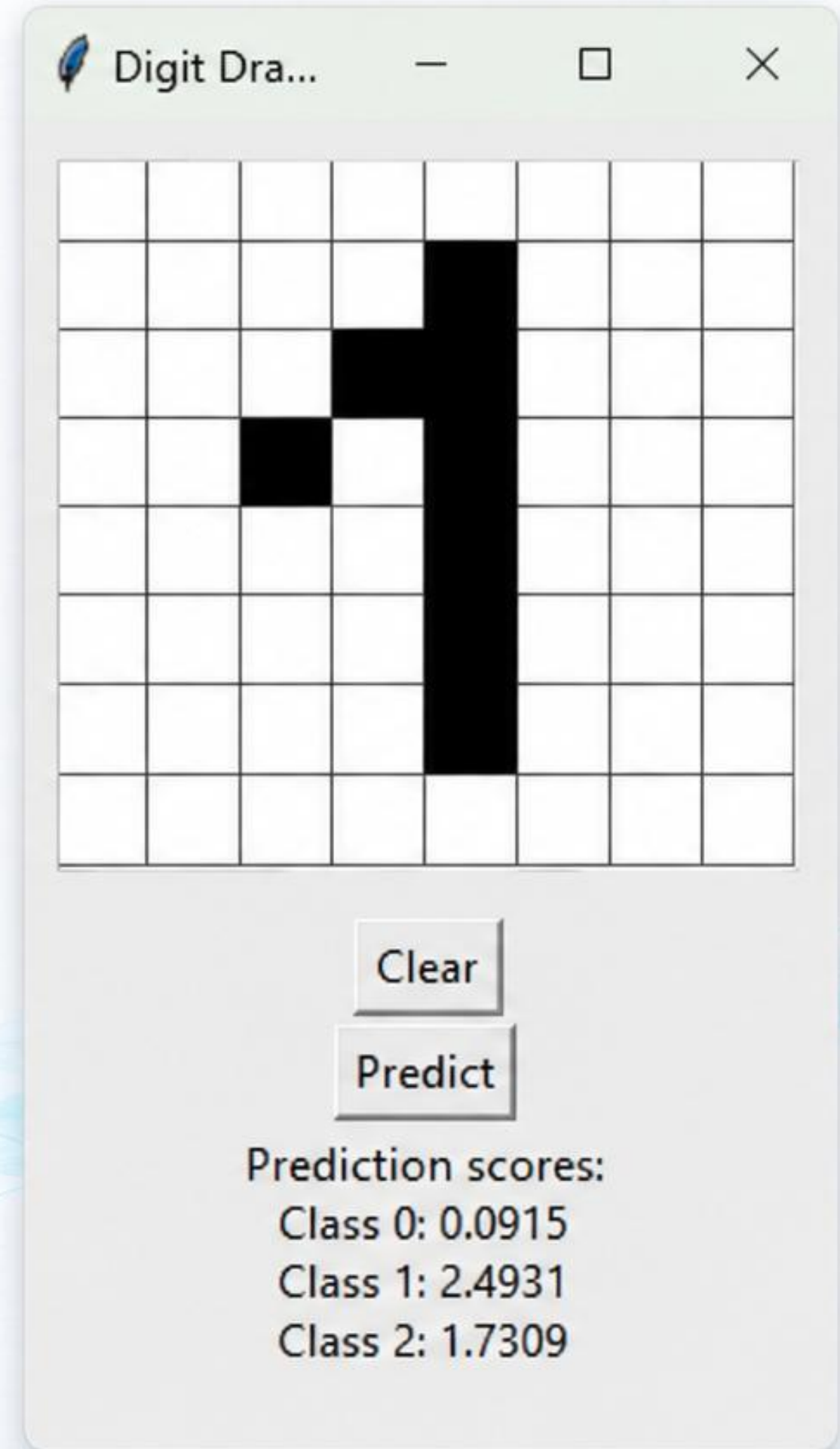


We built a simulation to evaluate the model's confidence level.

# Digital Proof of Concept

**80%  
Classification  
Accuracy**

**Key Insight:** Digital prediction scores translate into physical water levels.

A software window titled "Digit Dra..." with standard window controls (minimize, maximize, close). It features a 10x10 grid where a handwritten digit '4' is drawn using black pixels. Below the grid are two buttons: "Clear" and "Predict". Under the "Predict" button, the text "Prediction scores:" is followed by three lines of data: "Class 0: 0.0915", "Class 1: 2.4931", and "Class 2: 1.7309".

| Class   | Score  |
|---------|--------|
| Class 0 | 0.0915 |
| Class 1 | 2.4931 |
| Class 2 | 1.7309 |



# The Prototype

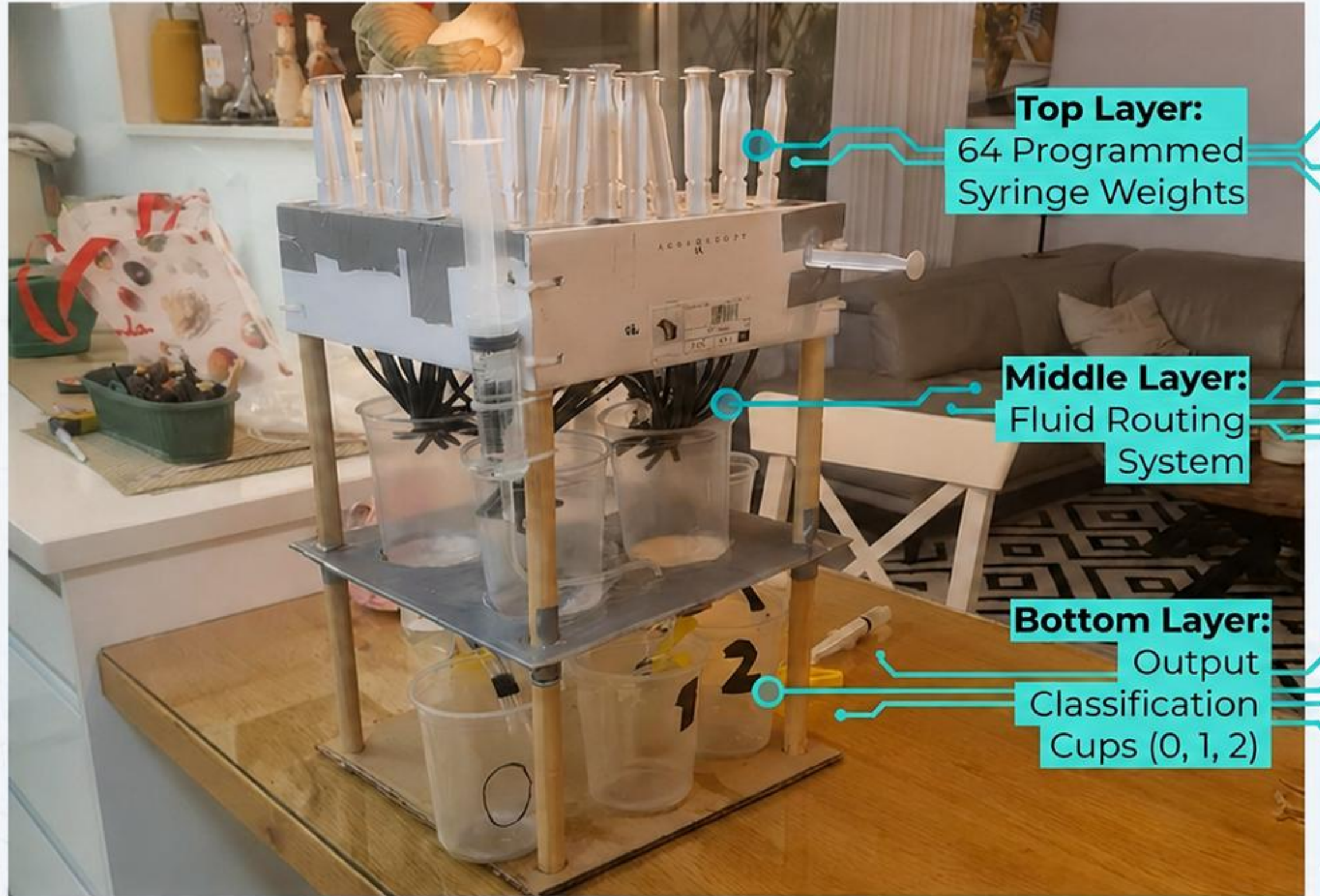
# The Input Matrix: 64-Neuron Initialization



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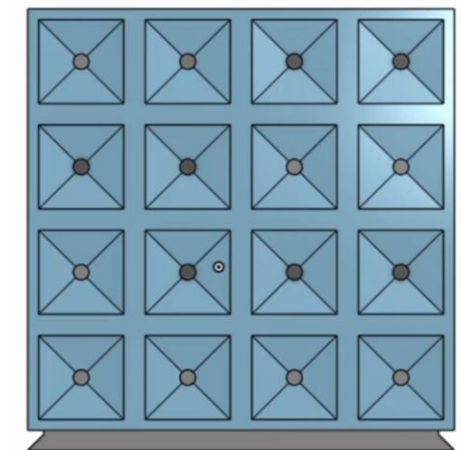
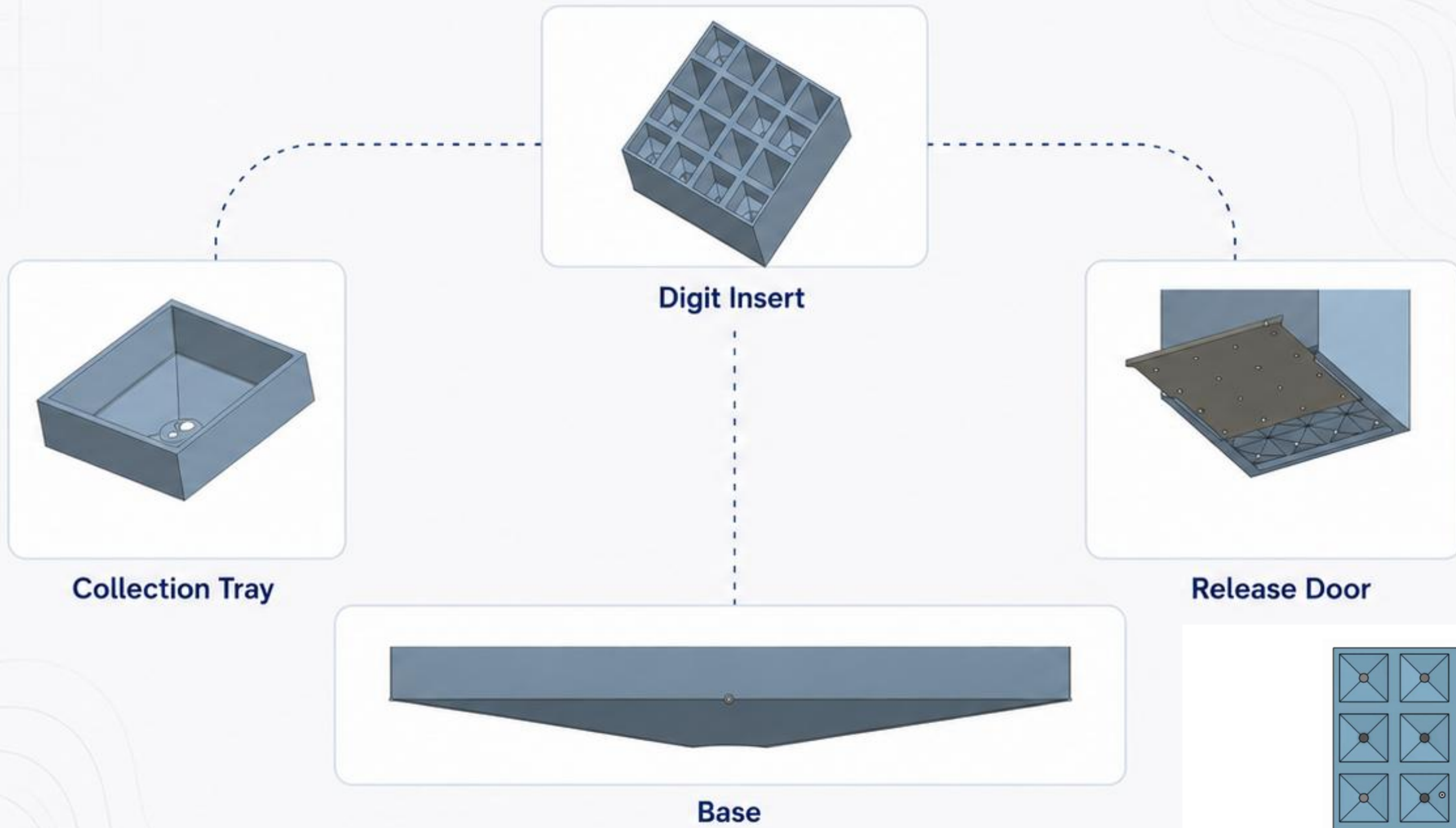


# The prototype : a water based neural network



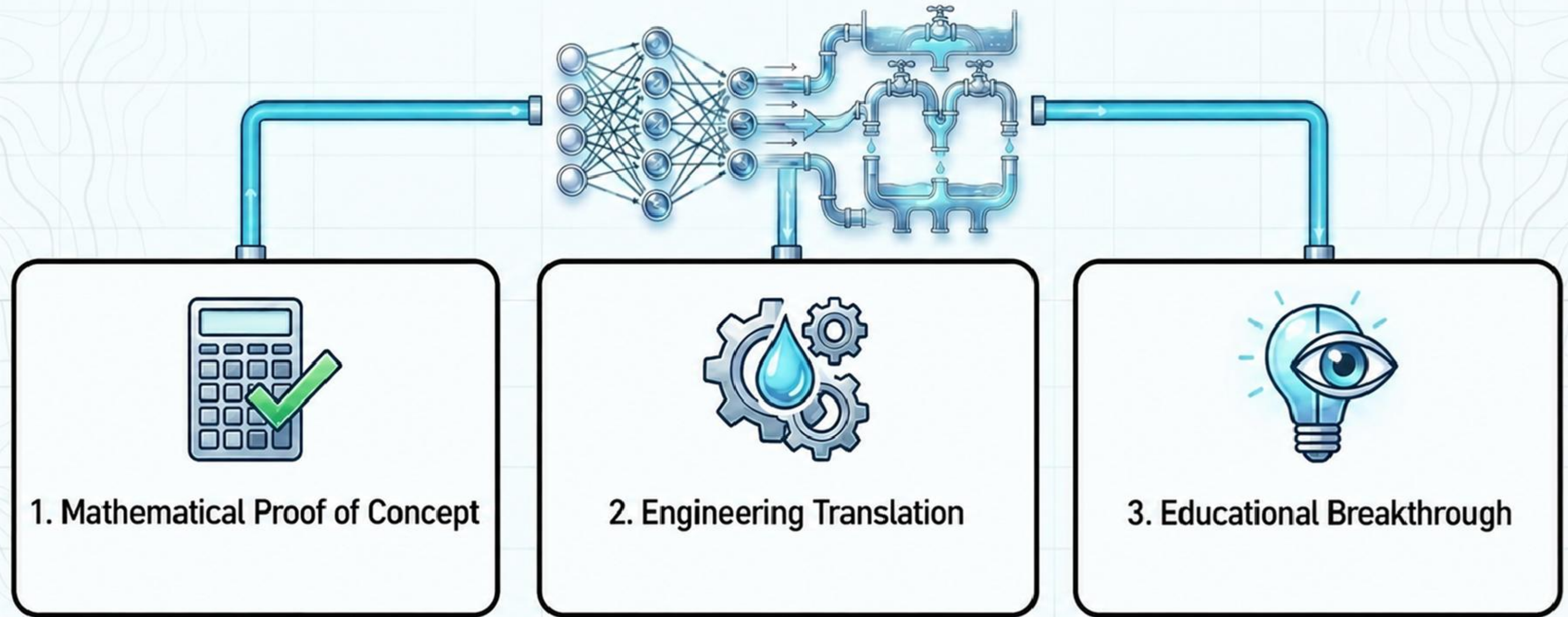


# What We Built



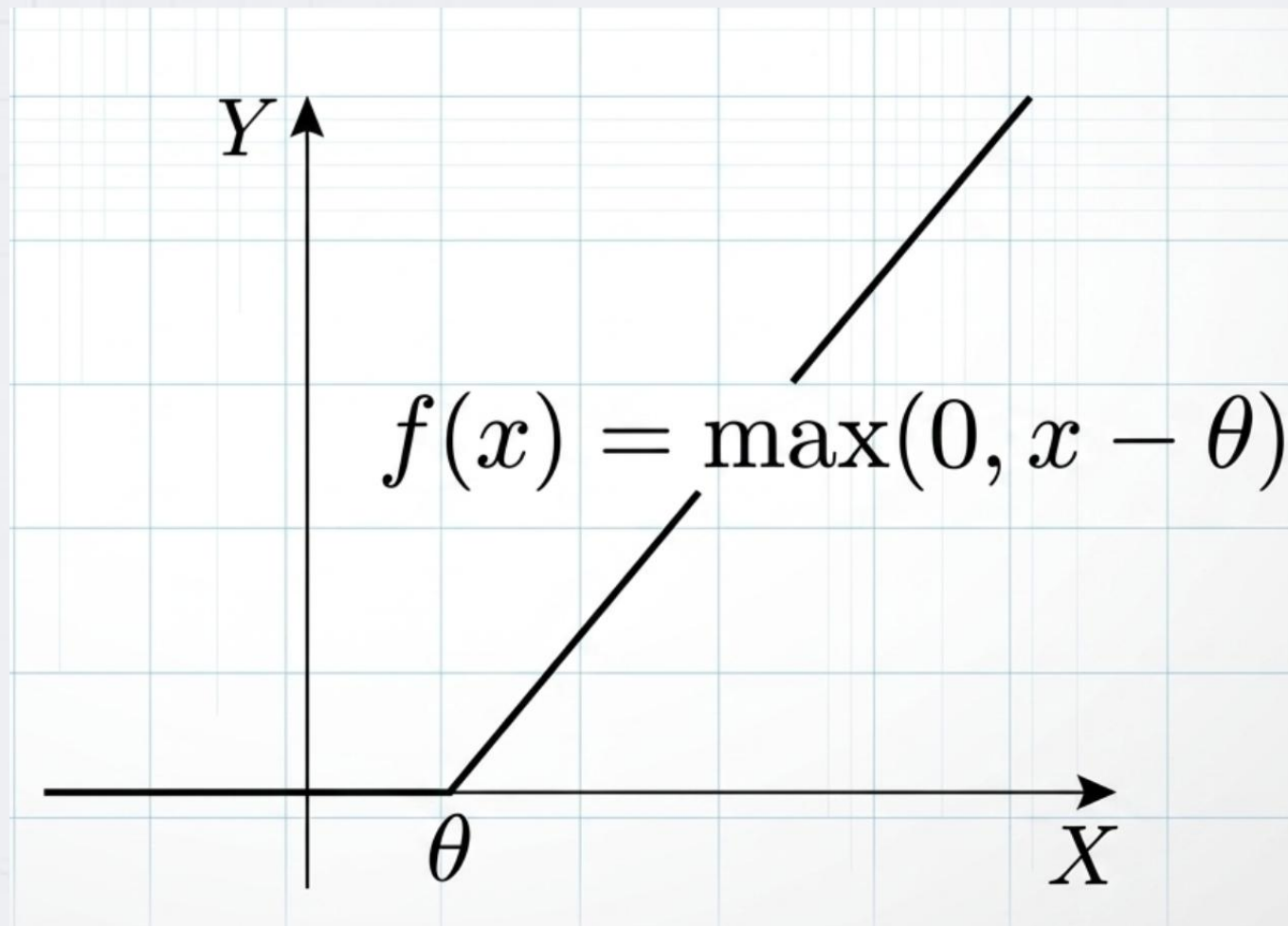
# Conclusion: Bridging the Abstraction Barrier

Proving computational logic via fluid mechanics

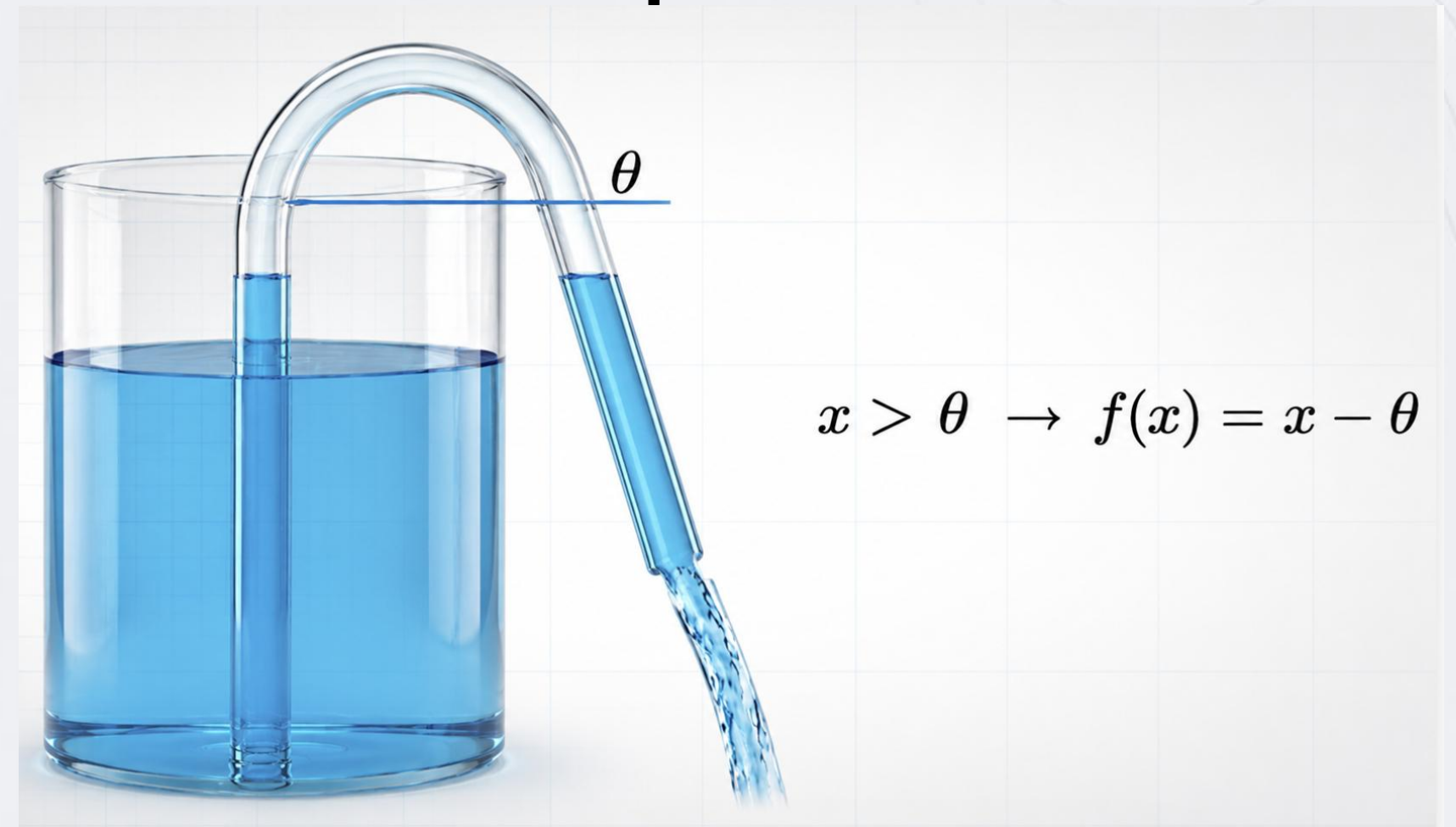


# Future Work

ReLU Function

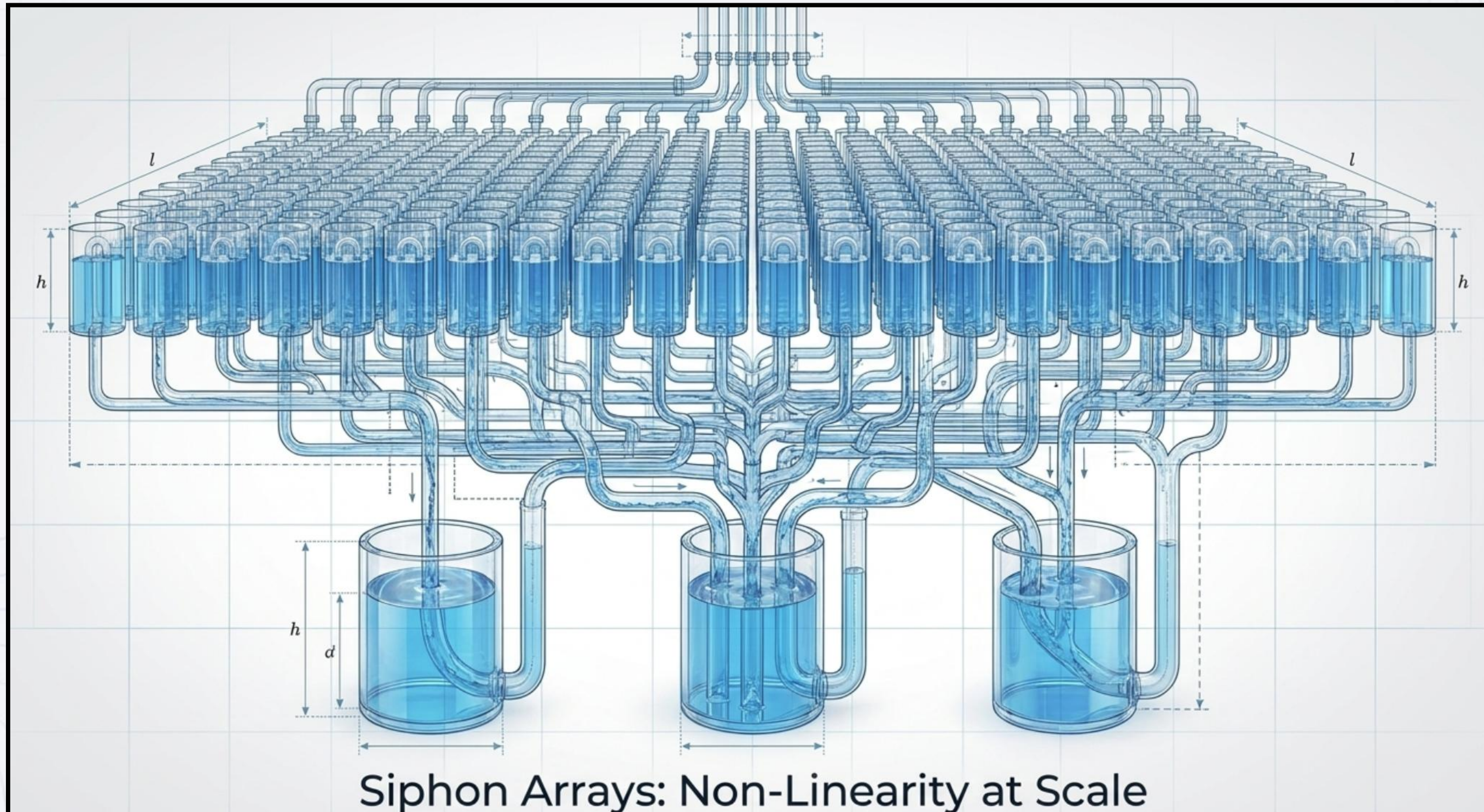


Siphon

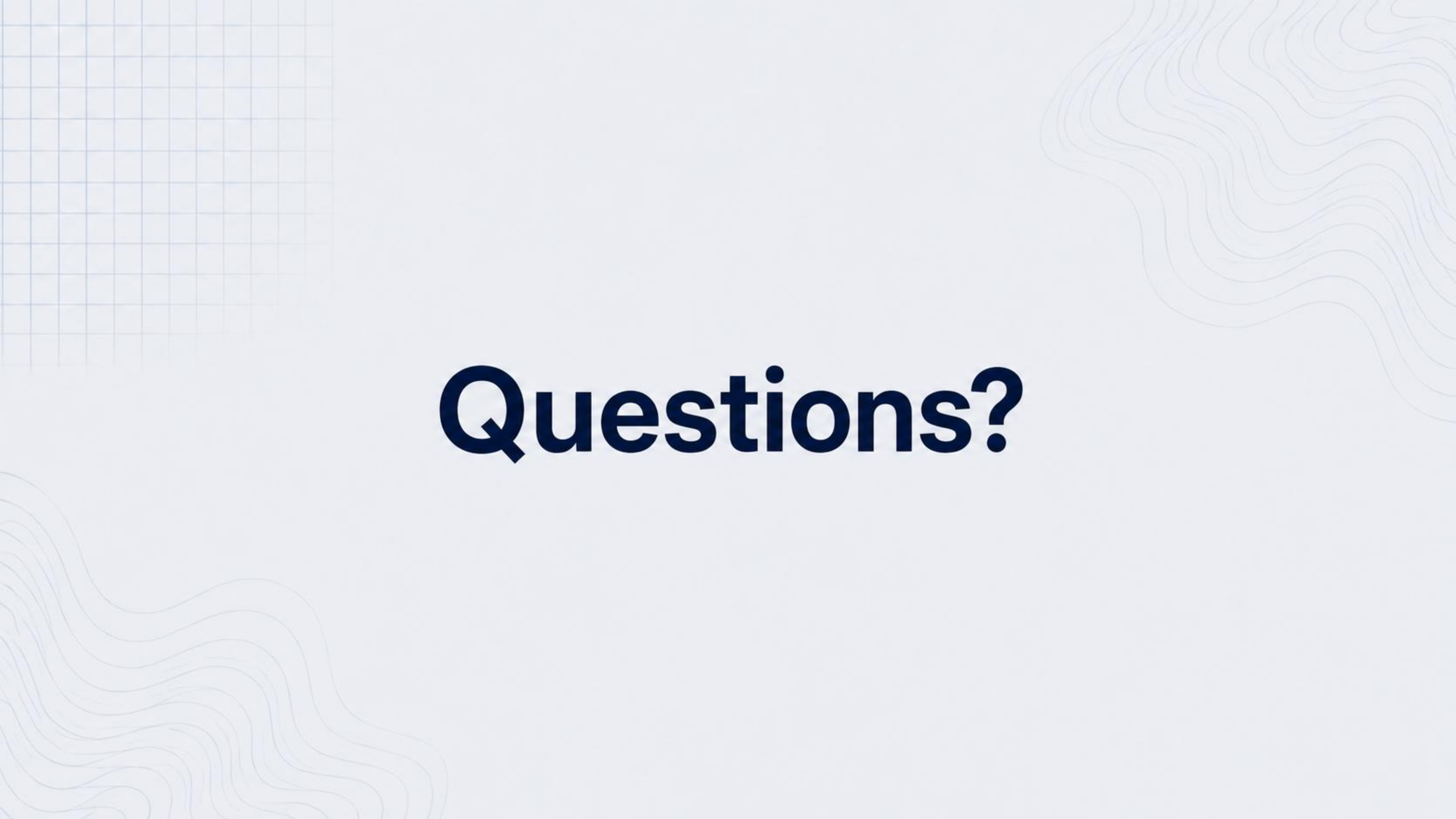


# Future Work

Leverage the universal approximation capability of ReLU networks to achieve arbitrarily high precision and build fully sized model.







**Questions?**