

# ANN Mathematical Process from Scratch for Paddy Yield Prediction

## Dataset

- **Samples:** 2,789
- **Input Features (X):** 45 (Climatic, Soil, Farm Management, Land area, County)
- **Target (y):** Paddy yield

## Data Preprocessing:

1. Missing & duplicate values removed
2. Wind direction: Sin-Cos encoding
3. Management inputs: Input  $i = c_i \cdot \text{Hectares}$ ; excluded if redundant
4. Feature scaling: Z-score normalization for continuous variables  $(X_{ij} - \text{np.mean}(X_j)) / \text{np.std}(X_j)$
5. Categorical: One-hot encoding

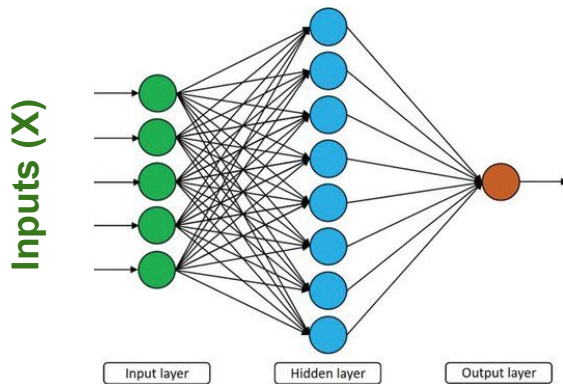
**Research Hypothesis:** ANN can predict paddy yield accurately by capturing nonlinear relationships among climate, soil, and agronomic factors.

## Artificial Neural Network Architecture

### Forward Propagation

$$X \cdot W1 = Z1 \Rightarrow A1 = \tanh(Z1) \Rightarrow \\ \Rightarrow A1 \cdot W2 = Z2 \Rightarrow y_{\text{pred}} = \text{linear}(Z2)$$

**Parameter Update**  
 $W1 := W1 - \eta \frac{\partial L}{\partial W1}$   
 $W2 := W2 - \eta \frac{\partial L}{\partial W2}$



**Loss Function**  
$$\text{MSE} = 1 / n \sum (y_i - y_{\text{pred}})^2 \text{ for } (i = 1 \text{ to } n)$$

### Backpropagation & Parameter update

$$\frac{\partial L}{\partial W2} = \frac{\partial L}{\partial y_{\text{pred}}} \cdot \frac{\partial y_{\text{pred}}}{\partial Z2} \cdot \frac{\partial Z2}{\partial W2} \\ \frac{\partial L}{\partial W1} = \frac{\partial L}{\partial y_{\text{pred}}} \cdot \frac{\partial y_{\text{pred}}}{\partial Z2} \cdot \frac{\partial Z2}{\partial A1} \cdot \frac{\partial A1}{\partial Z1} \cdot \frac{\partial Z1}{\partial W1}$$

# ANN - Experimental Setup & Training Conditions

$X_{\text{train}} \in [-2.09, 2.00]$

$y_{\text{train}} \in [-1.85, 1.77]$

$\eta = 0.01 / 0.001$

Standard Normal:  $W \sim N(0,1)$

Xavier Initialisation:  $W = \text{randn}(\cdot) \sqrt{1 / n_{\text{inputs}}}$  and  $\sqrt{1 / n_{\text{hidden}}}$

$Z_1 \in [-1.44, 1.42]$

$Y_{\text{pred}} \in [-0.43, +0.43]$

Batch Gradient Descent

Epoch: 1000

Exp No	Architecture	A1	Output	Train MSE Scaled (Forward Pass)	Train MSE Scaled (After one step Gradient descent)	Test MSE (Scaled)	RMSE (Kg)	Relative RMSE (%)
B. 1	43 / 1/ 1	tanh	linear	1.0581	1.054	1.0144	9311.2	41.00%
B. 2	43 / 1/1	Sigmoid	linear	1.0343	1.0336	0.9954	9223.4	40.61%
B. 3	43 / 1/1	Relu	linear	1.0541	1.0506	1.0048	9266.89	40.80%
B. 4	43 / 1/1	Linear	linear	1.098	1.0868	1.0525	9484.35	41.76%
B. 5	43 / 1/1	Linear	Tanh	1.092	1.082	1.0473	9460.96	41.65%
Exp No	Architecture	A1	Output	Train MSE Scaled (Epoch 0)	Train MSE Scaled (Final step)	Test MSE (Scaled)	RMSE (Kg)	Relative RMSE (%)
6	43 / 1/ 1	Relu	linear	1.0581	0.1014	0.1023	2957.2	13.02%
7	43 / 1/1	Linear	linear	1.098	0.0138	0.014	1093.81	4.82%
8	43 / 5 / 1	tanh	linear	1.0668	0.0149	0.0136	2771.95	4.74%
9	43 / 5 / 1	linear	tanh	1.095	0.099	0.0899	2771.95	12.20%
10	43 / 30/ 1	tanh	linear	1.1159	0.011	0.0113	980.88	4.32%
11	43 / 30/ 1	Sigmoid	linear	1.8264	0.014	0.0139	1091.42	4.81%
12	43 /20/ 10 / 1	Tanh / tanh	linear	1.0521	0.0118	0.01225	1023.48	4.51%
13	43 /30 / 1	linear	linear	1.2378	0.0127	0.0125	1031.85	4.54%
14	43 / 30/ 1	tanh	linear	TensorFlow benchmark Models (for comparison)		0.0107	954.63	4.20%
15	43 /20/1	sigmoid	linear			0.0097	910.3	4.01%

# Gradient Descent Convergence for Top Models & Actual vs Predicted Plot for Best Model

