

Classification of Gas-Sensor Array Data using Machine Learning

Major Project
School of Mathematics

Project Supervisors
Dr. Dharmatti Sheetal
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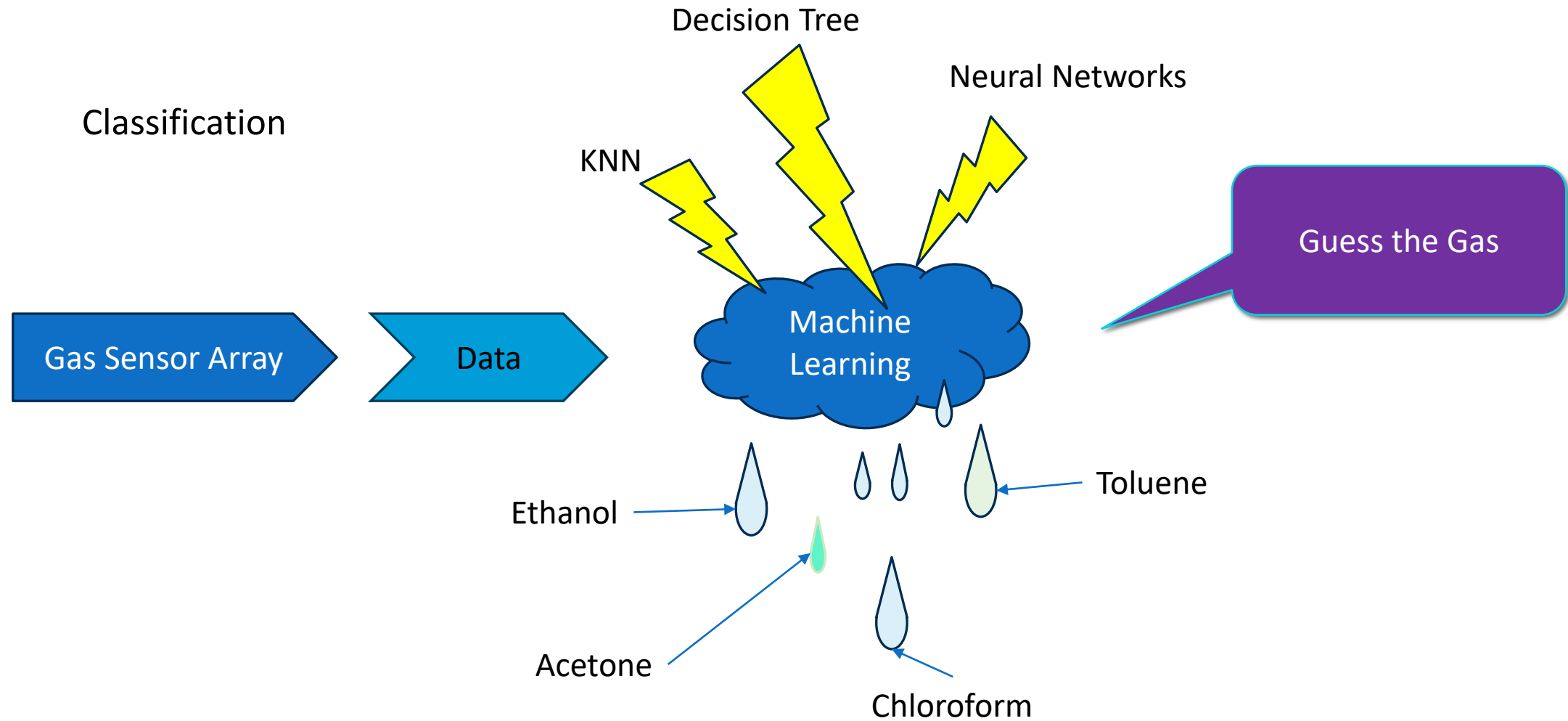


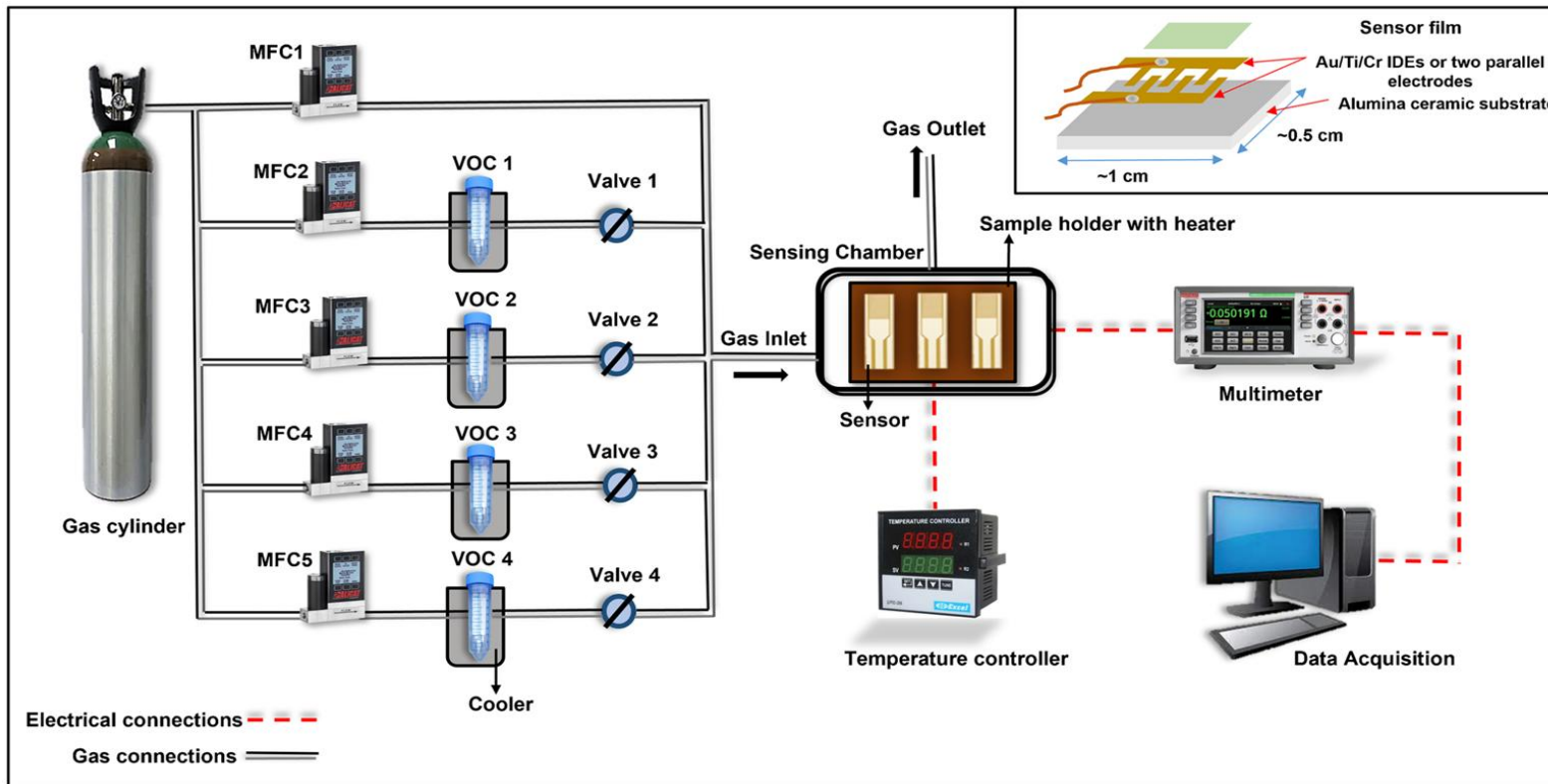
29-04-2024

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IMS19175

The Goal

Classification





Volatile Organic Compound(VOC)

	Resistance	Sensor	Temp	Conc	Gas
0	2032.37575	0	200.0	2400	2
1	2032.42944	0	200.0	2400	2
2	2032.60295	0	200.0	2400	2
3	2032.66493	0	200.0	2400	2
4	2032.65253	0	200.0	2400	2
...
2262999	100272.94300	2	350.0	1000	0
2263000	100295.06810	2	350.0	1000	0
2263001	100314.88840	2	350.0	1000	0
2263002	100335.92470	2	350.0	1000	0
2263003	100356.66760	2	350.0	1000	0
2263004	100377.81050	2	350.0	1000	0

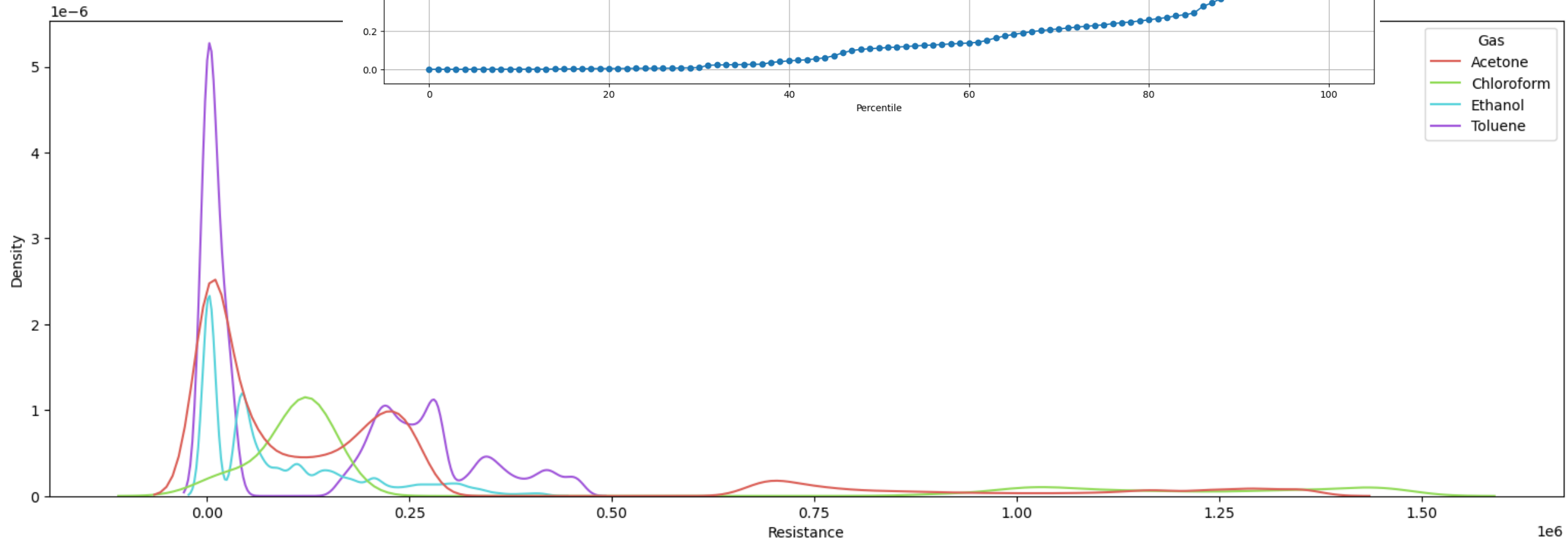
The schematic diagram of the gas sensing setup used for the experiment

S. Singh et al. "Metal oxide-based gas sensor array for VOCs determination in complex mixtures using machine learning". In: Microchimica Acta 191.4 (2024). Published online: March 13, 2024, pp. 1–10. doi: 10.1007/s00604 024-06258-8.

Resistance	Sensor	Temperature	Concentration	Gas
$10^3 - 10^6 \Omega$	<ol style="list-style-type: none"> NiO-Au(ohmic) CuO-Au(Schottky) ZnO-Au(Schottky) 			<ol style="list-style-type: none"> Ethanol Acetone Toluene Chloroform

Preprocessing

K-Density Plot



22L points

Scaling (0-1)

Input features

	Resistance	Sensor	Temp	Conc	Gas
0	2032.37575	0	200.0	2400	2
1	2032.42944	0	200.0	2400	2
2	2032.60295	0	200.0	2400	2
3	2032.66493	0	200.0	2400	2
4	2032.65253	0	200.0	2400	2
...
2262999	100272.94300	2	350.0	1000	0
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2263002	100335.92470	2	350.0	1000	0
2263003	100356.66760	2	350.0	1000	0
2263004 rows × 5 columns					

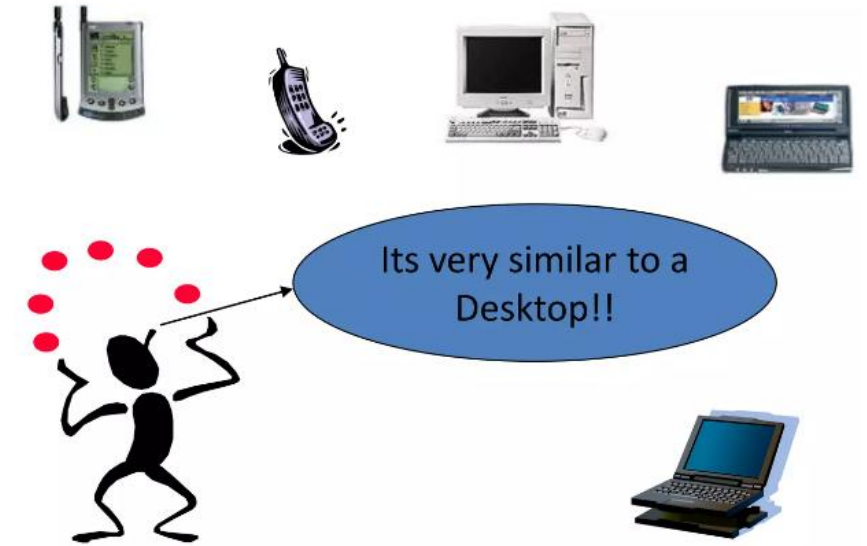
Min-Max Scaler



	Resistance	Sensor	Temp	Conc	Gas
0	0.000789	0	0.0	0.888807	2
1	0.000789	0	0.0	0.888807	2
2	0.000789	0	0.0	0.888807	2
3	0.000789	0	0.0	0.888807	2
4	0.000789	0	0.0	0.888807	2
...
2262999	0.067206	2	1.0	0.369904	0
2263000	0.067221	2	1.0	0.369904	0
2263001	0.067235	2	1.0	0.369904	0
2263002	0.067249	2	1.0	0.369904	0
2263003	0.067263	2	1.0	0.369904	0
2263004 rows × 5 columns					

KNN(K Nearest Neighbor)

- non-parametric, lazy learning algorithm
- classification and regression tasks.
- it doesn't build a model explicitly. Instead, it stores all available cases and classifies new cases based on their similarity to existing cases.



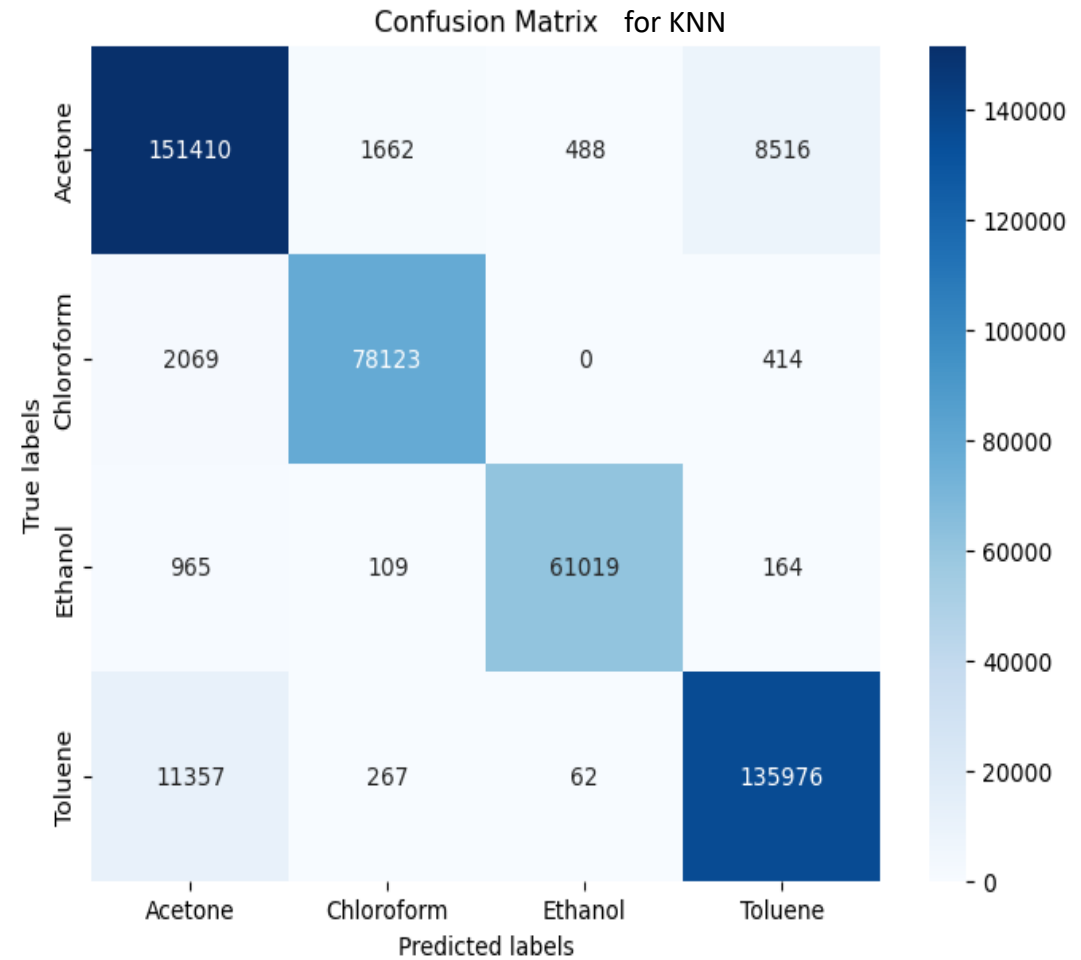
Given a dataset with labeled points,

- classifies new data points by finding the 'K' nearest neighbors in the training data.
- **Classification** the majority class among the K neighbors is assigned to the new data point.
- **Regression** the output value for the new point is calculated as the average of the values of its K nearest neighbors.



KNN

K	5
Train Data Points	18 lac
Test Data points	4 lac
Accuracy	0.942523
Training Time	18s
Test time	21s



Gini impurity, measures the impurity of a set of labels.

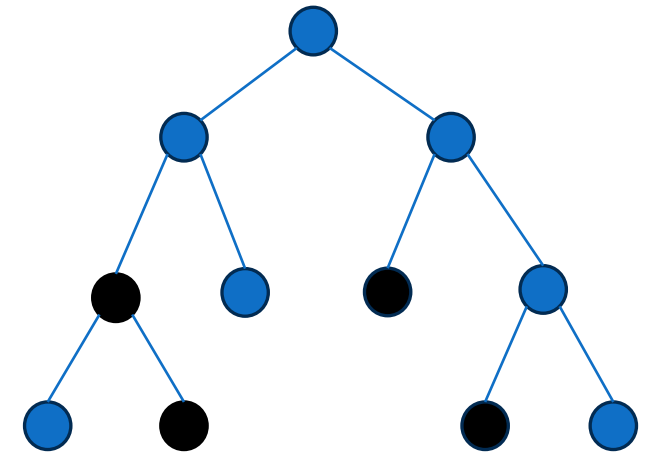
For a set **S** with **N** data points and **K** classes, the Gini impurity **G(S)** is calculated as:

$$G(S) = 1 - \sum_{i=1}^K P_i^2$$

where P_i is the probability of class **K** in set **S**.



Find the split that minimizes the impurity of the resulting subsets.



Decision tree

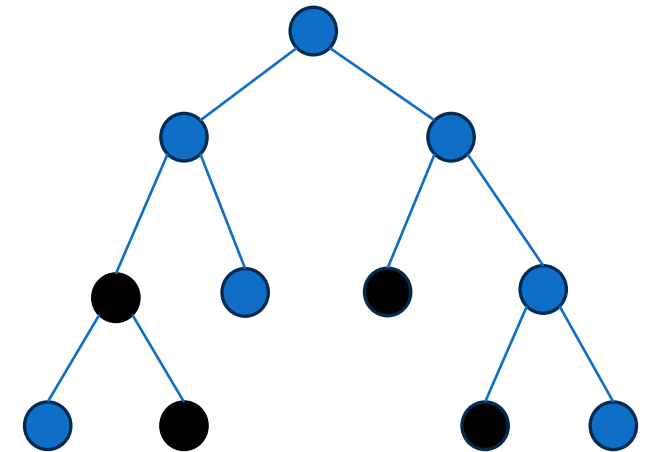
Decision Tree

Suppose, we have a dataset with two features X_1 and X_2 and four classes [0, 1, 2, 3]

At each node, the algorithm selects the best feature and threshold to split the data based on the Gini impurity.

For example, at the root node, it might choose X_1 with a threshold of 0.5 to split the data into two subsets.

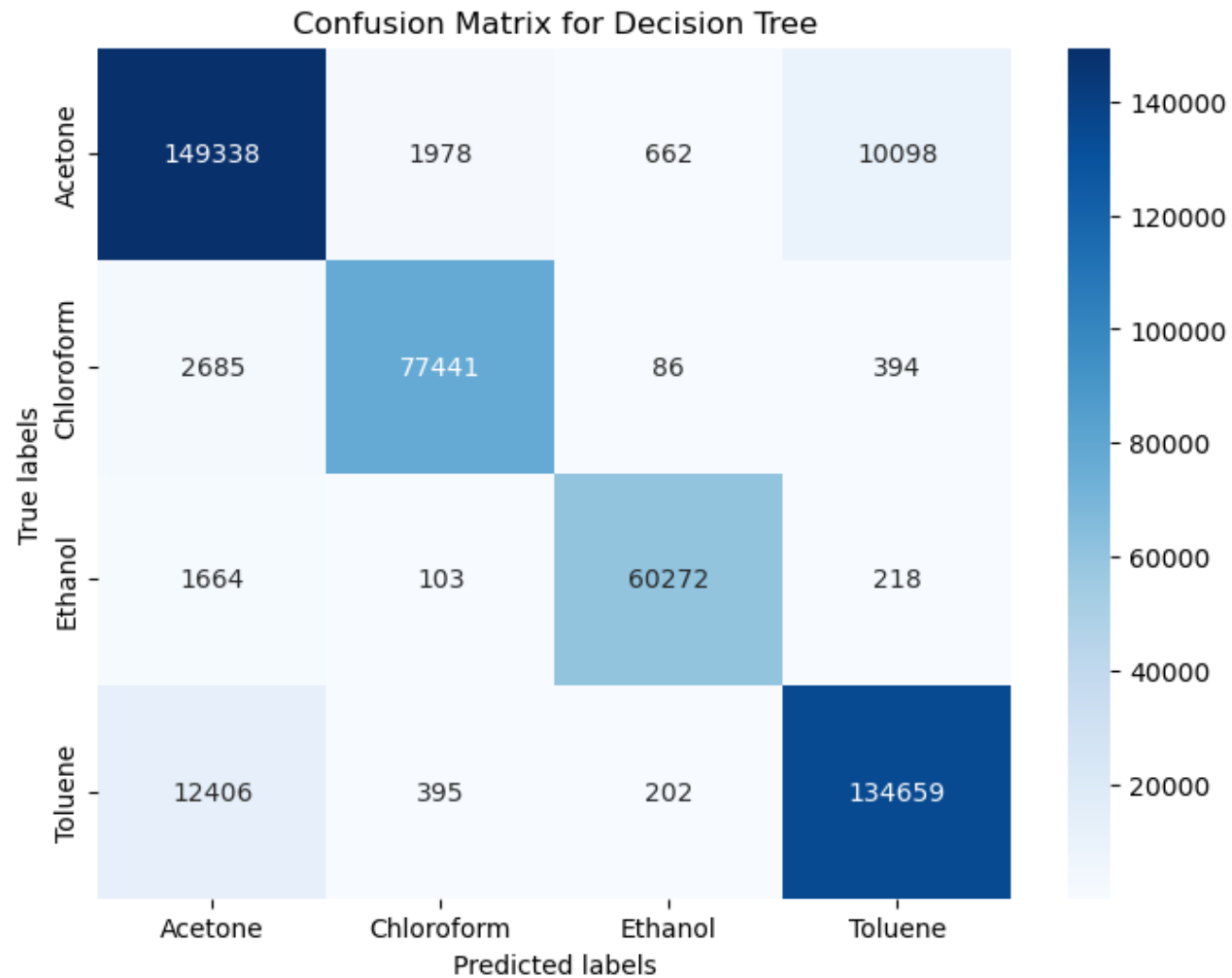
continues recursively until leaf nodes are reached, forming a tree structure.



Decision tree

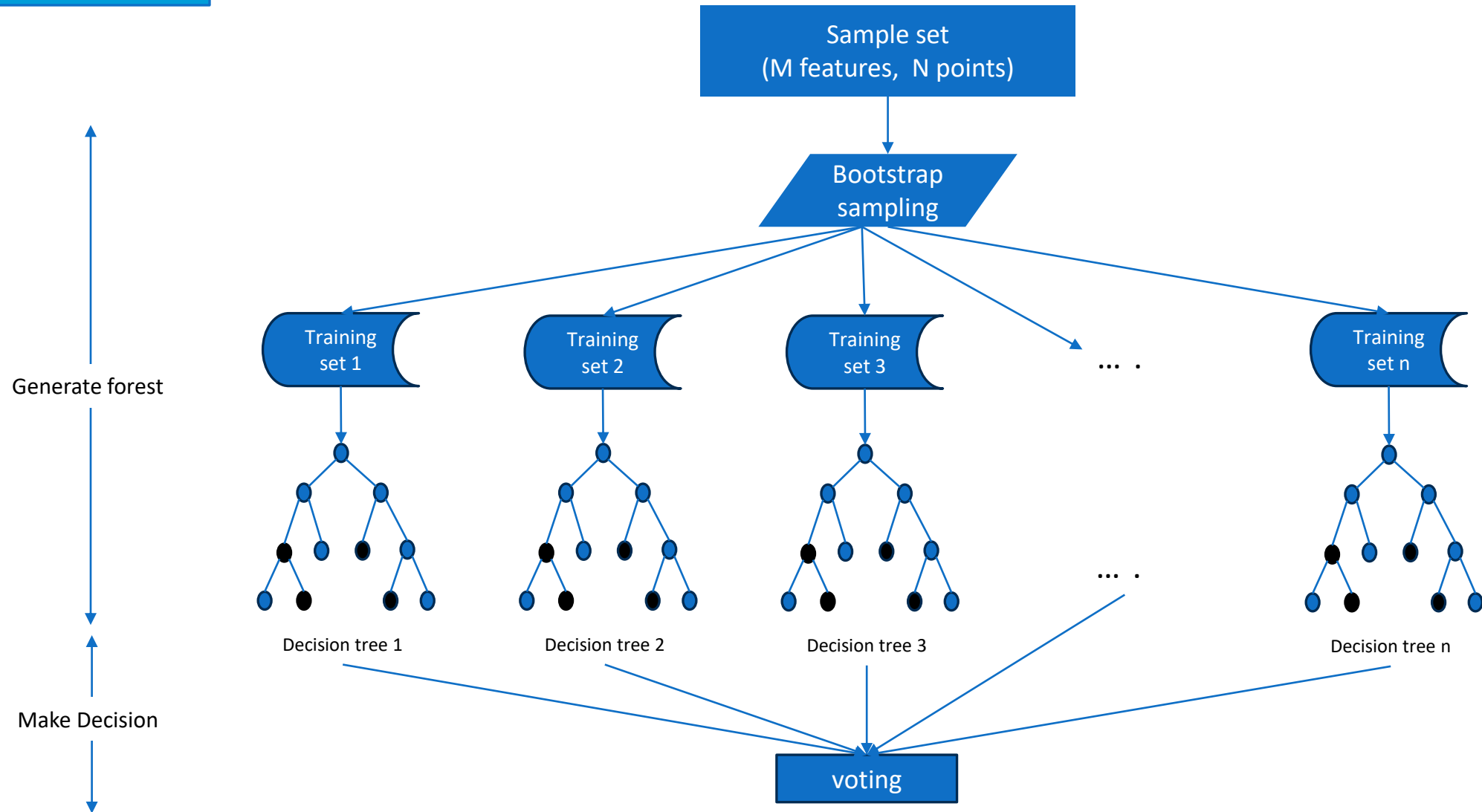
Decision Tree

Train Data Points	18 lac
Test Data points	4 lac
Accuracy	0.9317
Training Time	3s
Test time	~0s



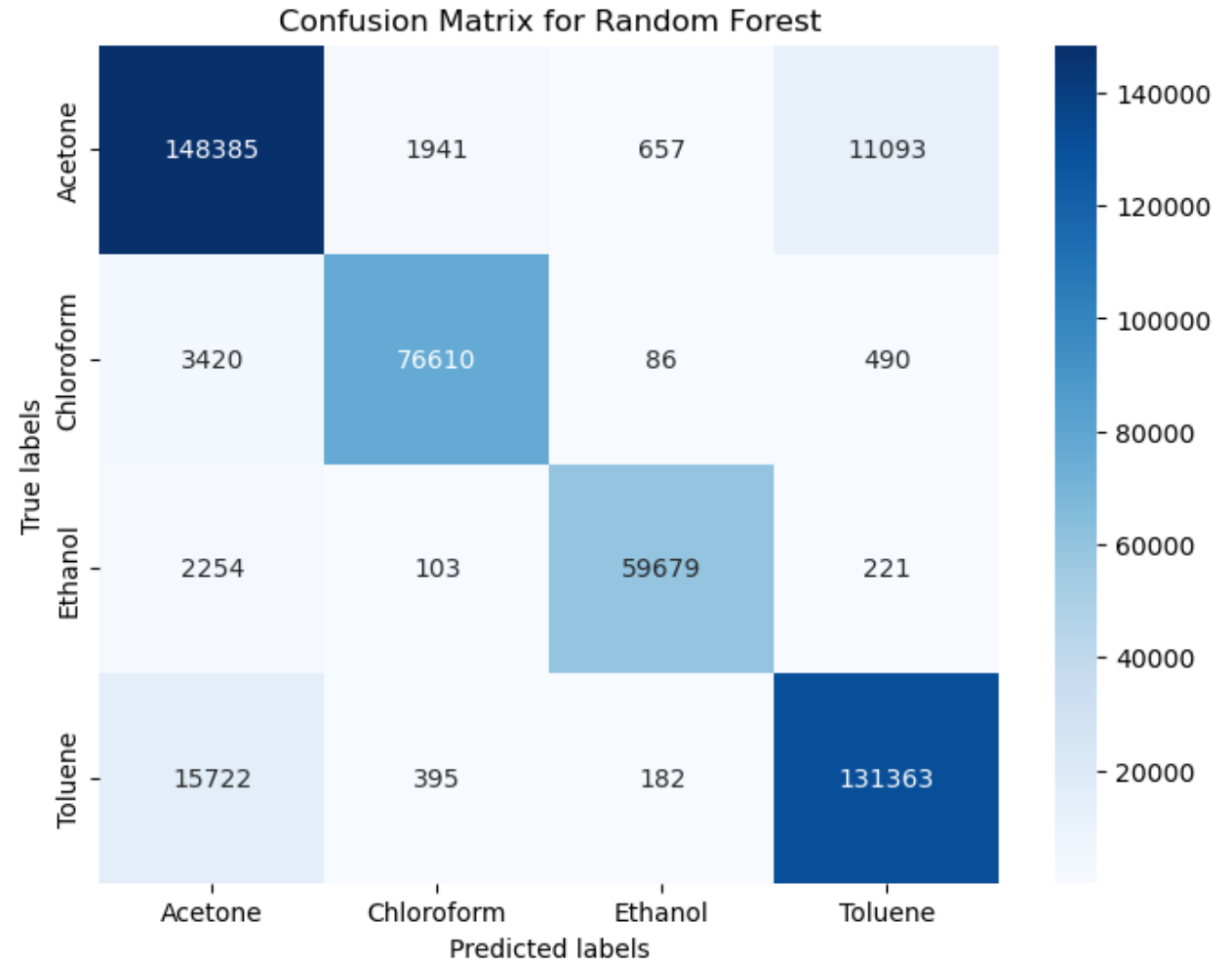
- Random forest is an ensemble classifier which uses many decision trees.
- It builds multiple decision trees and merges them together to get more accurate and stable prediction.
- It can be used for both classification and regression problems

Random Forest



Random Forest

Train Data Points	18 lac
Test Data points	4 lac
Accuracy	0.9192
Training Time	2m10s
Test time	5s

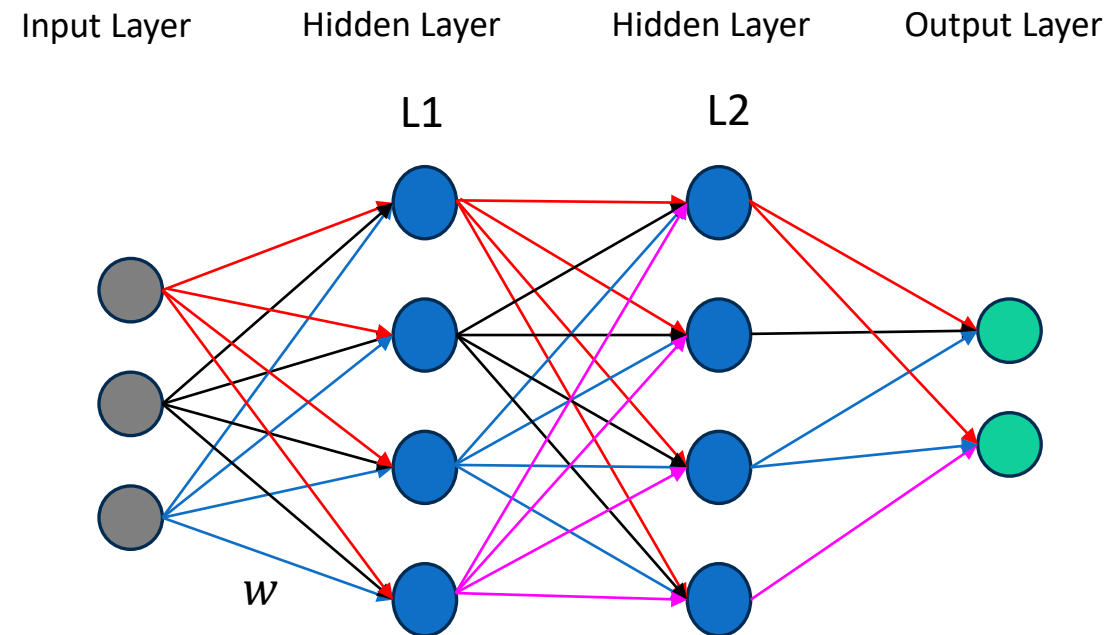


Biological Model

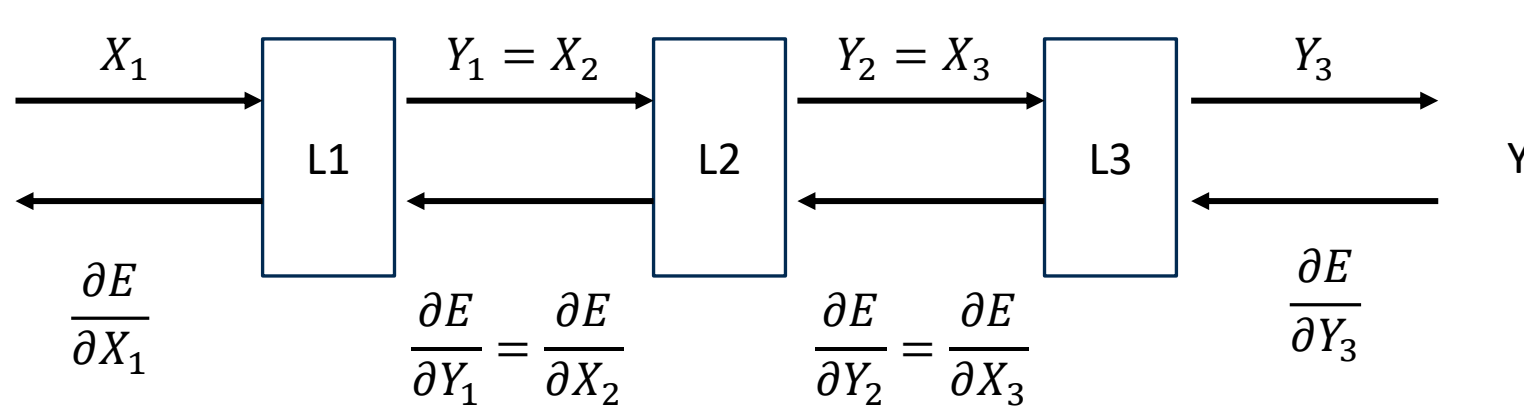
- **Neuron:** an excitable cell
- **Synapse:** connection between neurons
- **electrochemical pulse**
- **collection of neurons** along some pathway through the brain

Artificial Model

- **Neuron:** node
- **Weight:** multiplier on each edge
- **Activation Function**
- **collection of neurons** define some differentiable function



$$Y = \text{network}(X, W)$$



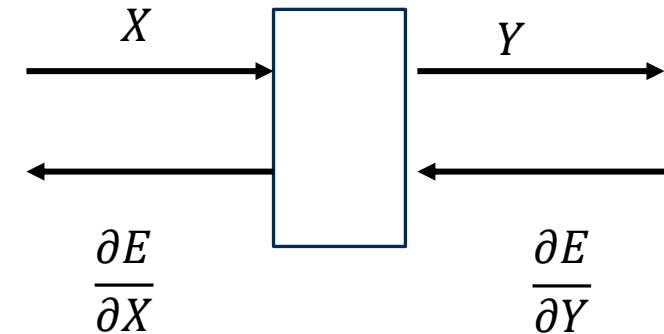
Y^* -desired output
 Y -actual output

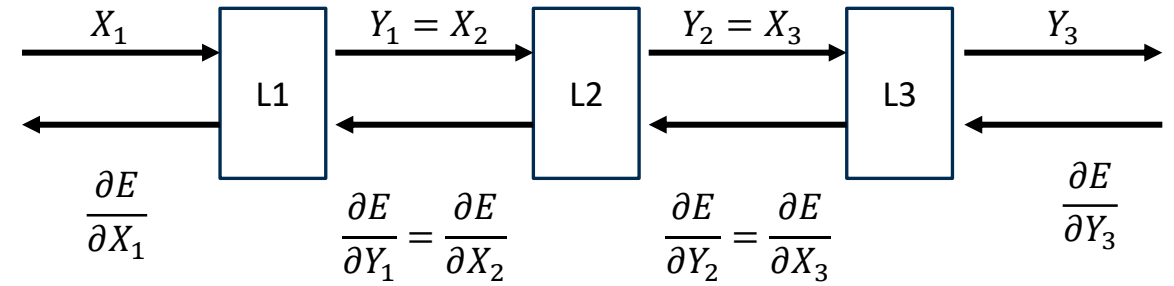
Calculate the Error (MSE),

$$E = \frac{1}{2} (Y^* - Y)^2$$

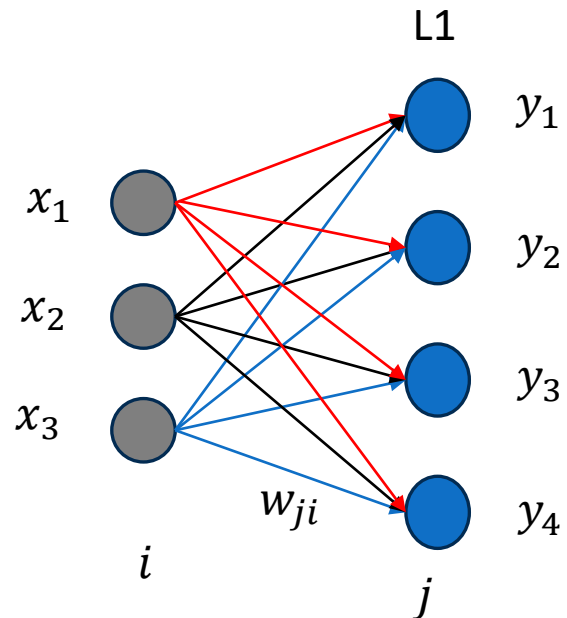
Adjust the parameters using gradient descent

$$W \rightarrow W - \alpha \frac{\partial E}{\partial W} \quad \frac{\partial E}{\partial W} = \frac{\partial E}{\partial Y} \frac{\partial Y}{\partial W} \quad \frac{\partial E}{\partial X} = \frac{\partial E}{\partial Y} \frac{\partial Y}{\partial X}$$





Input Layer Hidden Layer



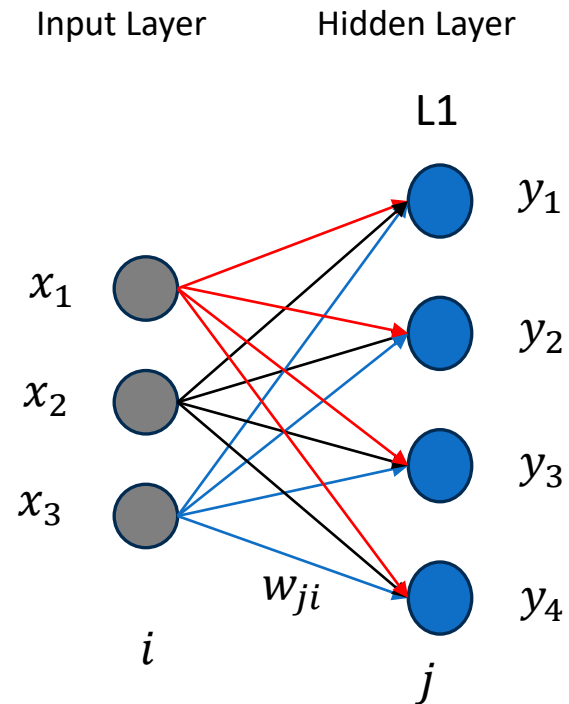
$$y_1 = w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + b_1$$

$$y_2 = w_{21}x_1 + w_{22}x_2 + w_{23}x_3 + b_2$$

$$y_3 = w_{31}x_1 + w_{32}x_2 + w_{33}x_3 + b_3$$

$$y_4 = w_{41}x_1 + w_{42}x_2 + w_{43}x_3 + b_4$$

w_{ji} are the weights



$$y_1 = w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + b_1$$

$$y_2 = w_{21}x_1 + w_{22}x_2 + w_{23}x_3 + b_2$$

$$y_3 = w_{31}x_1 + w_{32}x_2 + w_{33}x_3 + b_3$$

$$y_4 = w_{41}x_1 + w_{42}x_2 + w_{43}x_3 + b_4$$

w_{ji} are the weights

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \\ w_{41} & w_{42} & w_{43} & w_{44} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \\ w_{41} & w_{42} & w_{43} & w_{44} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}$$

$$y_1 = w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + b_1$$

$$y_2 = w_{21}x_1 + w_{22}x_2 + w_{23}x_3 + b_2$$

$$y_3 = w_{31}x_1 + w_{32}x_2 + w_{33}x_3 + b_3$$

$$y_4 = w_{41}x_1 + w_{42}x_2 + w_{43}x_3 + b_4$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_j \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1i} \\ w_{21} & \cdot & & \cdot \\ \vdots & & \ddots & \vdots \\ w_{j1} & \cdot & \dots & w_{ji} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_j \end{bmatrix}$$

$$y_j = w_{j1}x_1 + w_{j2}x_2 + \dots + w_{ji}x_i + b_j \implies \frac{\partial y_j}{\partial w_{ji}} = x_i$$

$$\implies \frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial y_j} x_i$$

$$Y = W \cdot X + B$$

$$\frac{\partial E}{\partial Y} = \begin{bmatrix} \frac{\partial E}{\partial y_1} \\ \frac{\partial E}{\partial y_1} \\ \vdots \\ \frac{\partial E}{\partial y_j} \end{bmatrix} \quad \text{and} \quad \frac{\partial E}{\partial W} = \begin{bmatrix} \frac{\partial E}{\partial w_{11}} & \frac{\partial E}{\partial w_{12}} & \dots & \frac{\partial E}{\partial w_{1i}} \\ \frac{\partial E}{\partial w_{21}} & \cdot & & \cdot \\ \vdots & & \ddots & \vdots \\ \frac{\partial E}{\partial w_{j1}} & \cdot & \dots & \frac{\partial E}{\partial w_{ji}} \end{bmatrix}$$

$$\frac{\partial E}{\partial W} = \begin{bmatrix} \frac{\partial E}{\partial y_1} x_1 & \frac{\partial E}{\partial y_1} x_2 & \dots & \frac{\partial E}{\partial y_1} x_i \\ \frac{\partial E}{\partial y_2} x_1 & \cdot & & \cdot \\ \vdots & & \ddots & \vdots \\ \frac{\partial E}{\partial y_j} & \cdot & \dots & \frac{\partial E}{\partial y_j} x_i \end{bmatrix}$$

$$\frac{\partial E}{\partial W} = \begin{bmatrix} \frac{\partial E}{\partial y_1} x_1 & \frac{\partial E}{\partial y_1} x_2 & \dots & \frac{\partial E}{\partial y_1} x_i \\ \frac{\partial E}{\partial y_2} x_1 & . & & . \\ \vdots & & \ddots & \vdots \\ \frac{\partial E}{\partial y_j} & . & \dots & \frac{\partial E}{\partial y_j} x_i \end{bmatrix}$$

$$\frac{\partial E}{\partial W} = \begin{bmatrix} \frac{\partial E}{\partial y_1} \\ \frac{\partial E}{\partial y_2} \\ \vdots \\ \frac{\partial E}{\partial y_j} \end{bmatrix} \cdot [x_1 \quad x_2 \quad \dots \quad x_i]$$

$$\boxed{\frac{\partial E}{\partial W} = \frac{\partial E}{\partial Y} \cdot X^T}$$

$$\frac{\partial E}{\partial B} = \begin{bmatrix} \frac{\partial E}{\partial b_1} \\ \frac{\partial E}{\partial b_1} \\ \vdots \\ \frac{\partial E}{\partial b_j} \end{bmatrix}$$

$$y_j = w_{j1} x_1 + w_{j2} x_2 + \dots + w_{ji} x_i + b_j$$

$$\Rightarrow \frac{\partial y_j}{\partial b_j} = 1$$

$$\Rightarrow \frac{\partial E}{\partial b_j} = \frac{\partial E}{\partial y_j}$$

$$\Rightarrow \boxed{\frac{\partial E}{\partial B} = \frac{\partial E}{\partial Y}}$$

$$y_j = w_{j1}x_1 + w_{j2}x_2 + \dots + w_{ji}x_i + b_j$$

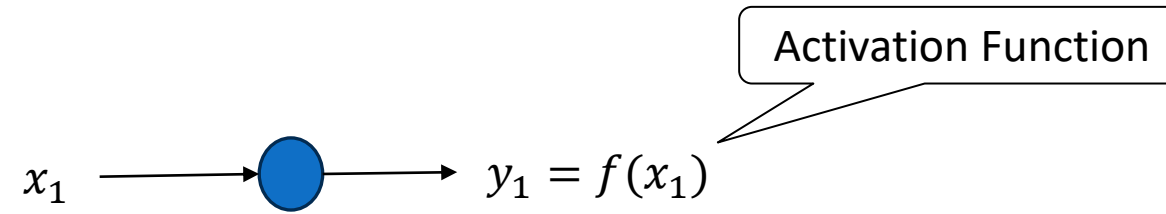
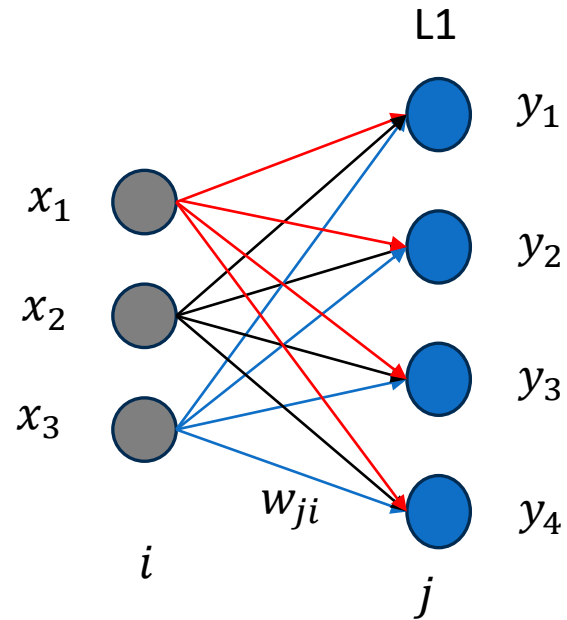
$$\frac{\partial E}{\partial x_i} = \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial x_i} \quad \left(\frac{\partial y_j}{\partial x_i} = w_{ji} \right)$$

$$\Rightarrow \frac{\partial E}{\partial x_i} = \frac{\partial E}{\partial y_j} w_{ji}$$

$$\frac{\partial E}{\partial X} = \begin{bmatrix} \frac{\partial E}{\partial x_1} \\ \frac{\partial E}{\partial x_2} \\ \vdots \\ \frac{\partial E}{\partial x_j} \end{bmatrix} = \begin{bmatrix} \frac{\partial E}{\partial y_1} w_{11} + \frac{\partial E}{\partial y_1} w_{21} + \dots + \frac{\partial E}{\partial y_1} w_{j1} \\ \frac{\partial E}{\partial y_2} w_{12} + \dots & \vdots \\ \frac{\partial E}{\partial y_j} w_{1j} + \dots + \frac{\partial E}{\partial y_j} w_{ji} \end{bmatrix}$$

$$\frac{\partial E}{\partial X} = \begin{bmatrix} w_{11} & w_{21} & \dots & w_{j1} \\ w_{12} & \cdot & \cdot & \cdot \\ \vdots & \cdot & \ddots & \vdots \\ w_{1j} & \cdot & \dots & w_{ji} \end{bmatrix} \begin{bmatrix} \frac{\partial E}{\partial y_1} \\ \frac{\partial E}{\partial y_1} \\ \vdots \\ \frac{\partial E}{\partial y_j} \end{bmatrix}$$

$$\boxed{\frac{\partial E}{\partial X} = W^T \cdot \frac{\partial E}{\partial Y}}$$



$$\frac{\partial E}{\partial X} = \begin{bmatrix} \frac{\partial E}{\partial x_1} \\ \frac{\partial E}{\partial x_2} \\ \vdots \\ \frac{\partial E}{\partial x_j} \end{bmatrix}$$

and

$$\frac{\partial E}{\partial x_i} = \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial x_i}$$

$$\frac{\partial E}{\partial x_i} = \frac{\partial E}{\partial y_j} f'(x_i)$$

$$\frac{\partial E}{\partial X} = \frac{\partial E}{\partial Y} \odot f'(X)$$

Calculate the Error (MSE),

Y^* -desired output
 Y -actual output

$$Y^* = \begin{bmatrix} y_1^* \\ y_2^* \\ \vdots \\ y_j^* \end{bmatrix}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_j \end{bmatrix}$$

$$\frac{\partial E}{\partial Y} = \begin{bmatrix} \frac{\partial E}{\partial y_1} \\ \frac{\partial E}{\partial y_1} \\ \vdots \\ \frac{\partial E}{\partial y_j} \end{bmatrix}$$

$$E = \frac{1}{n} \sum_{j=1}^n (y_j^* - y_j)^2$$

$$\frac{\partial E}{\partial y_j} = \frac{2}{n} (y_j^* - y_j)$$

$$\frac{\partial E}{\partial Y} = \frac{2}{n} (Y^* - Y)$$

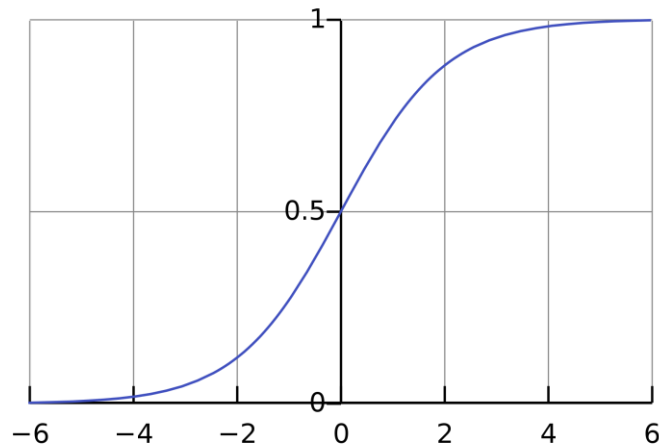
$$\frac{\partial E}{\partial Y} = \frac{2}{n} (Y^* - f(X))$$

$$\frac{\partial E}{\partial X} = \frac{\partial E}{\partial Y} \odot f'(X)$$

$$\frac{\partial E}{\partial X} = \left(\frac{2}{n} (Y^* - f(X)) \right) \odot f'(X)$$

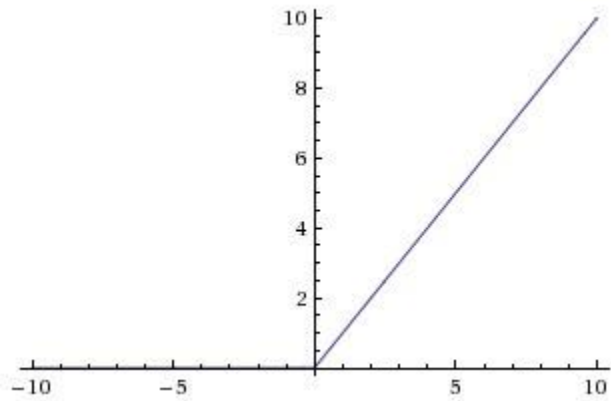
$$\frac{\partial E}{\partial W} = \left(\frac{2}{n} (Y^* - f(X)) \right) \cdot X^T$$

Sigmoid



$$S(x) = \frac{1}{1 + e^{-x}}$$

ReLU



$$f(x) = \max(0, x)$$

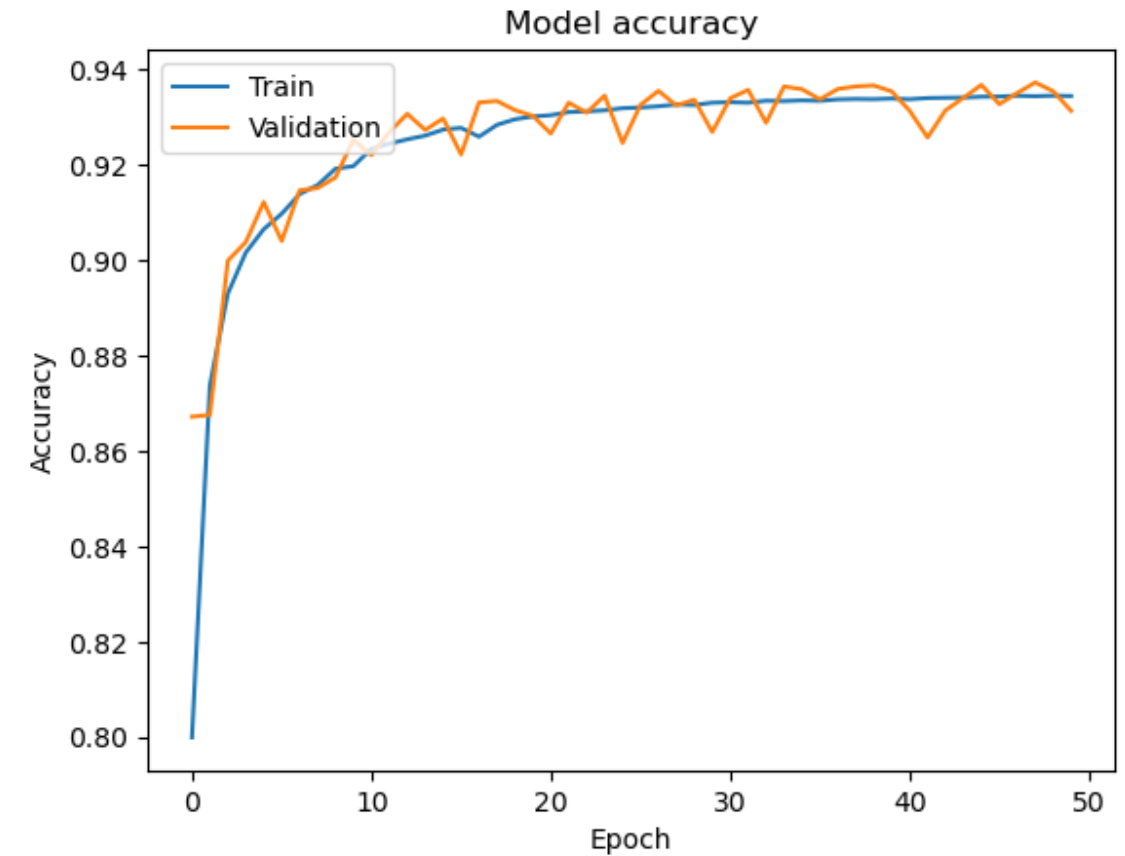
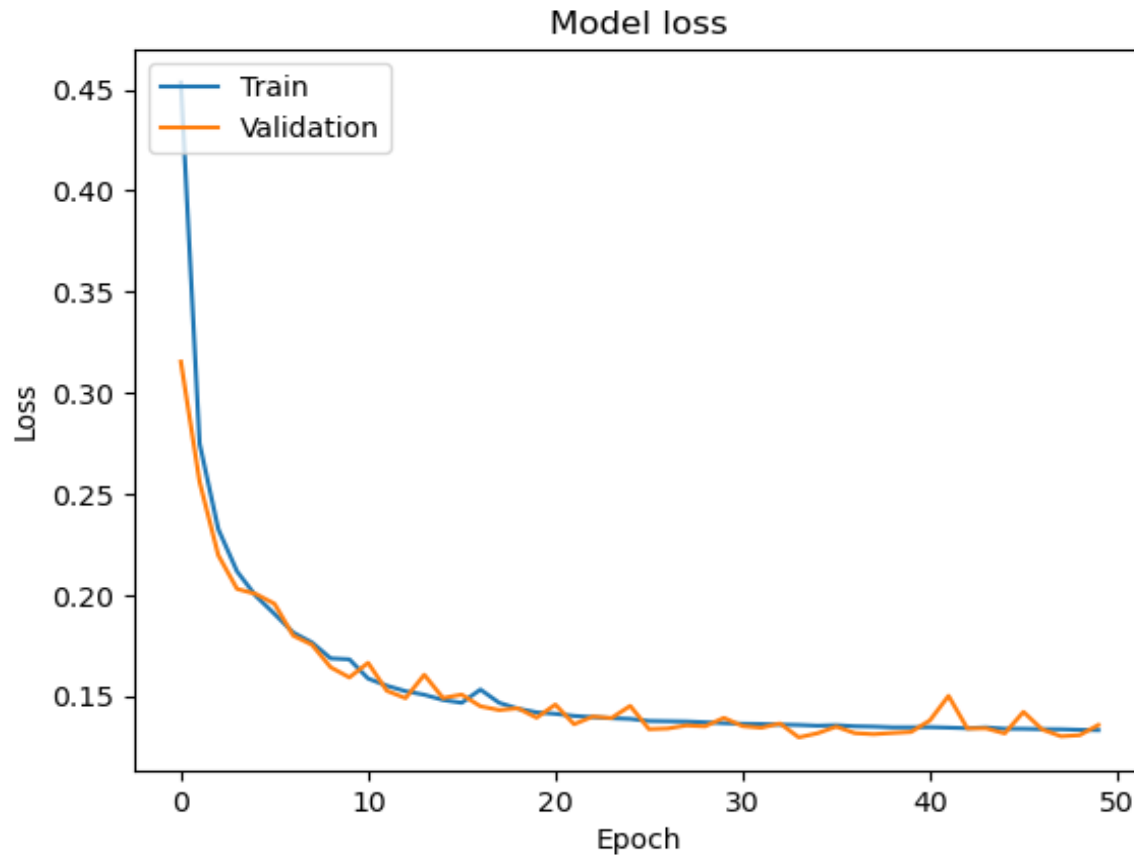
- The **batch size** is a number of samples processed before the model is updated.
- The number of **epochs** is the number of complete passes through the training dataset.

Neural Networks

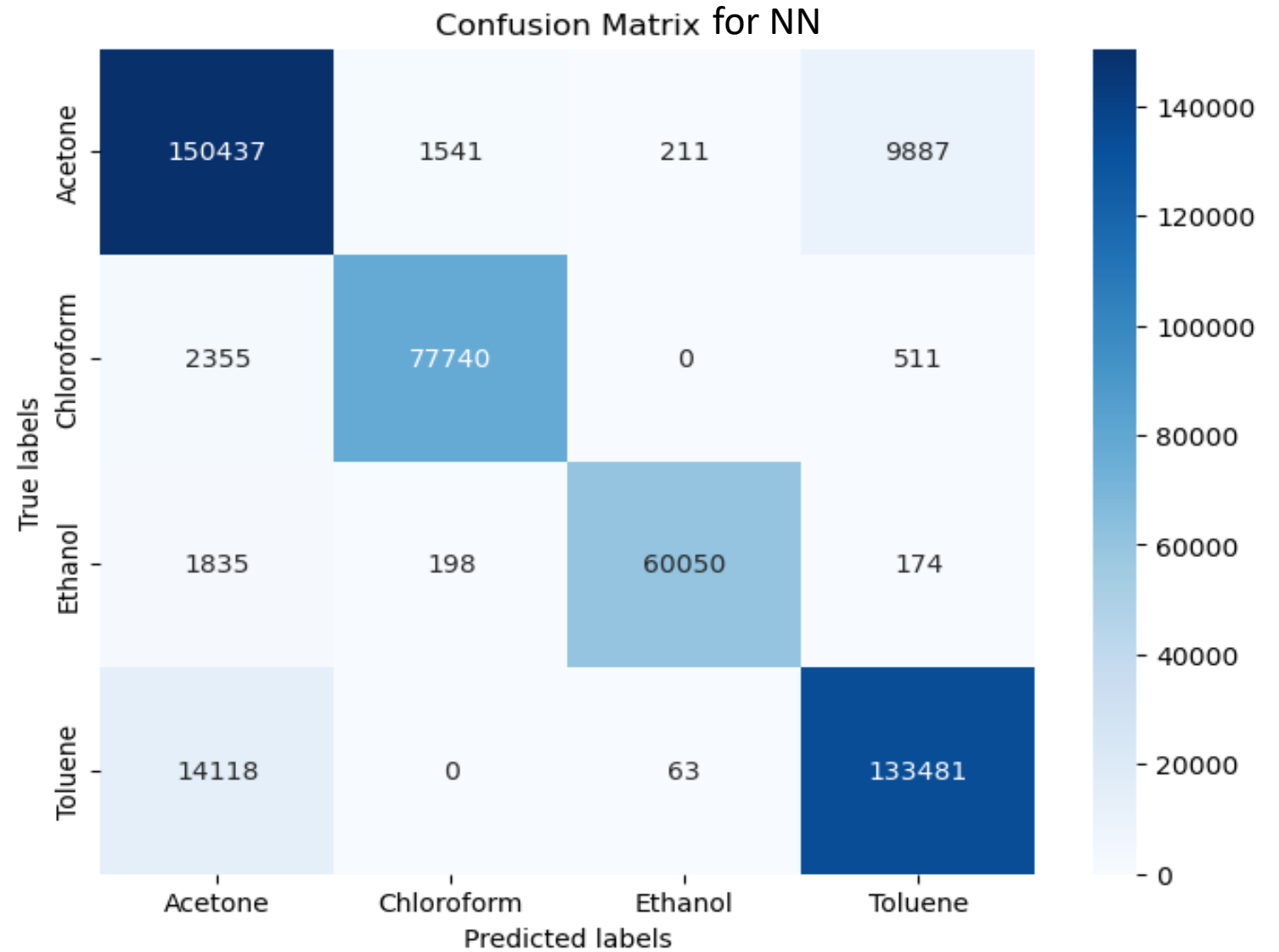
loss	0.1341156
Accuracy	0.93225824
Time	23m4s

epoch	50
Batch size	32
Validation split	0.1

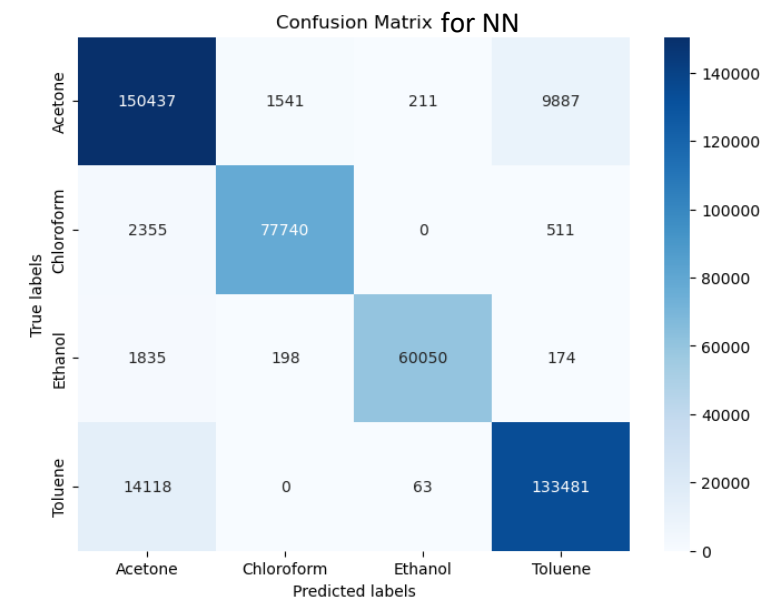
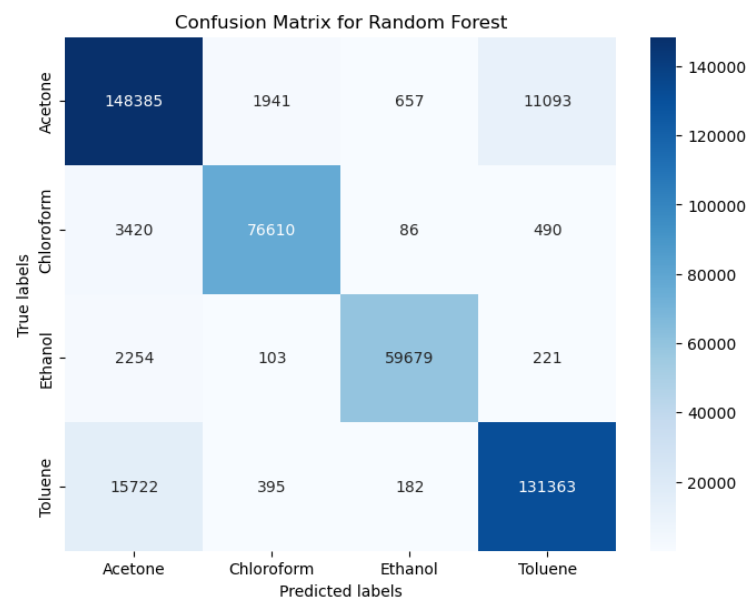
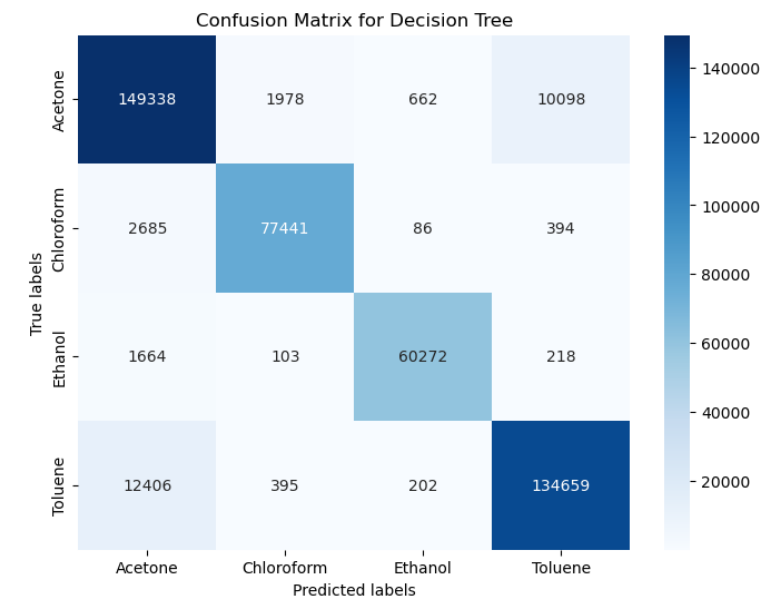
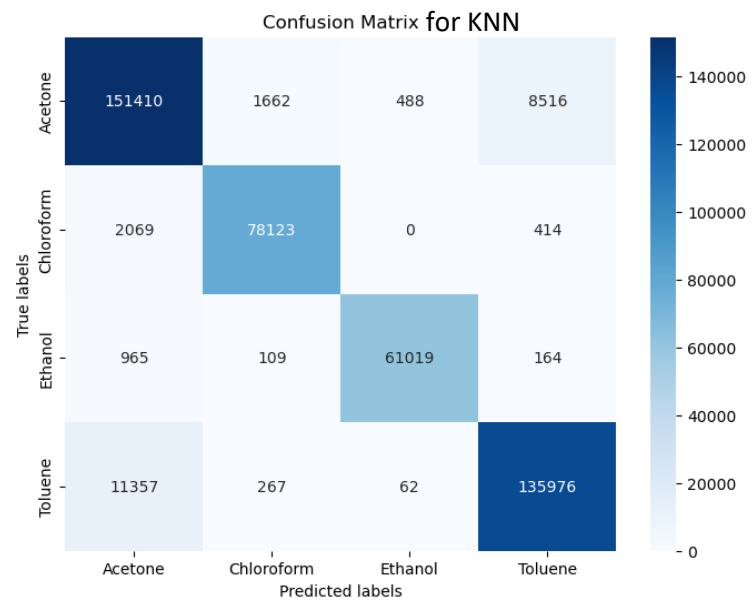
Model Training

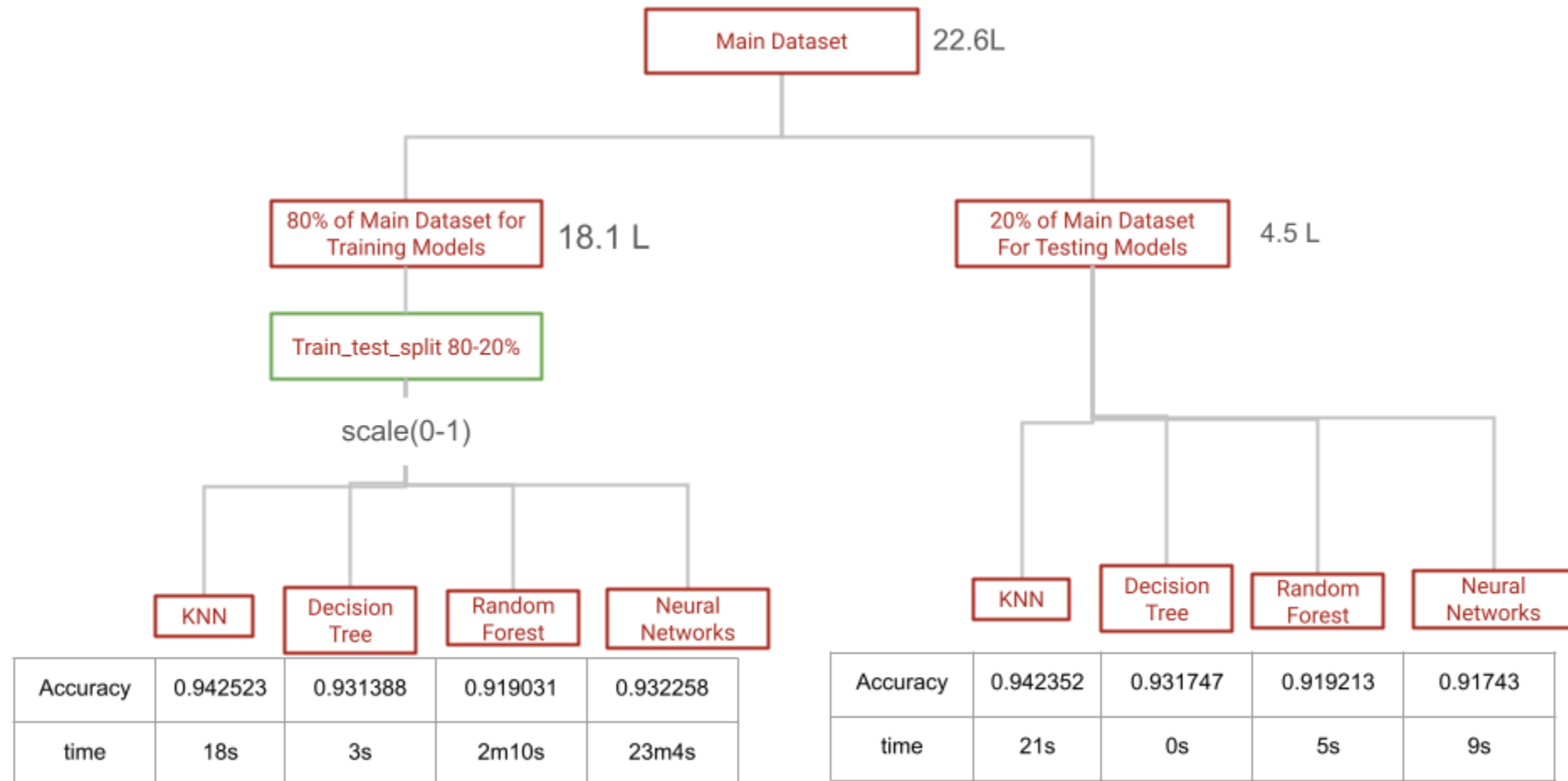


Train Data Points	18 lac
Test Data points	4 lac
Accuracy	0.91743
Training Time	23m
Test time	9s

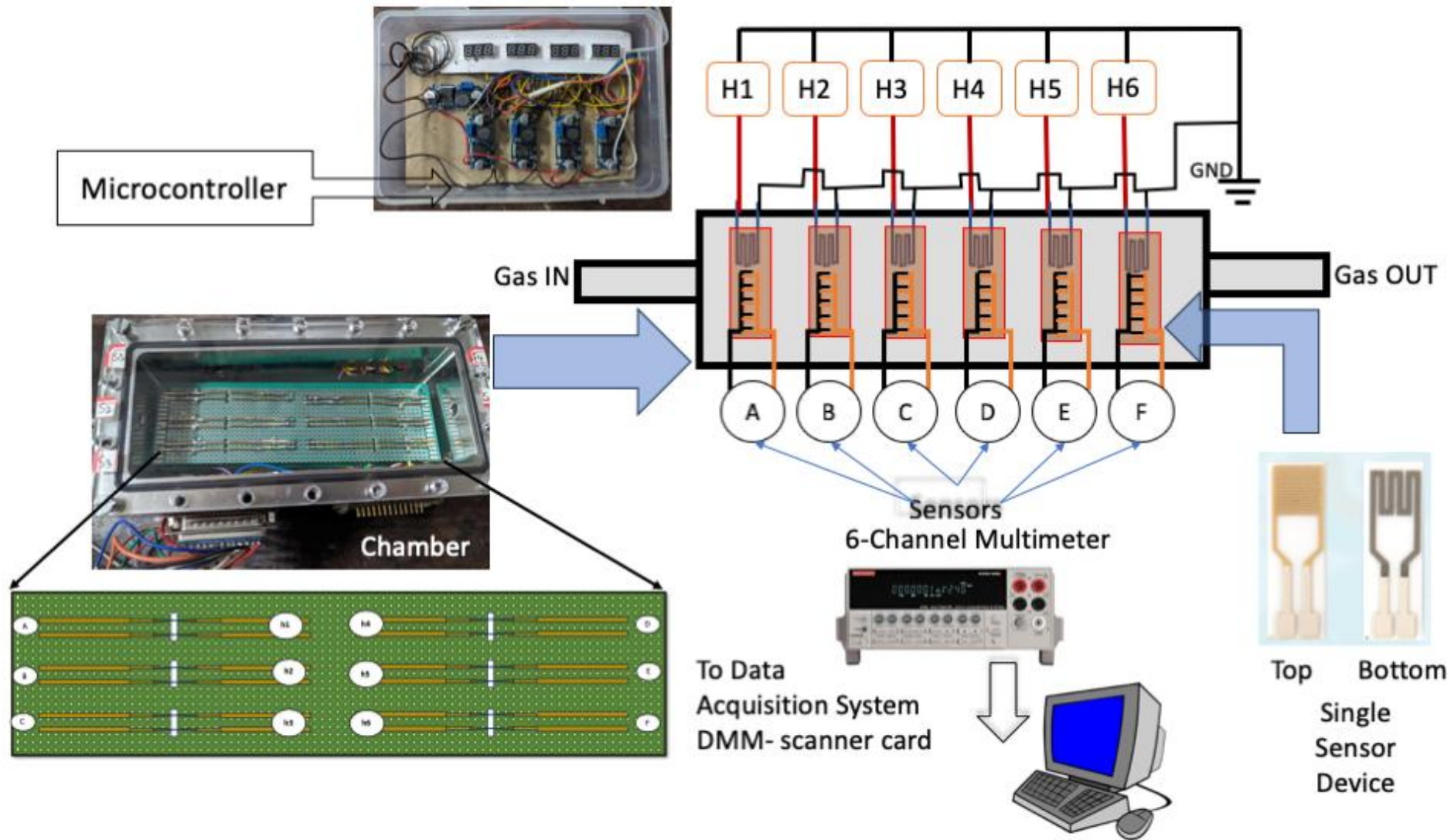


Results





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Conclusion

- PCA ~ Skew Results
- KNN, Decision tree, Random forest and NN. ✓
- accuracy of above 90%. ✓
- New Six Sensor Setup. ✓