

SPPU



MACHINE LEARNING

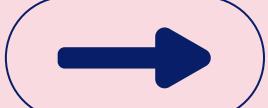
UNIT 6

INTRODUCTION TO NEURAL NETWORKS



Contents

- Artificial Neural Networks: Single Layer Neural Network
- Multilayer Perceptron
- Back Propagation Learning
- Functional Link Artificial Neural Network
- Radial Basis Function Network
- Activation functions,
- Introduction to Recurrent Neural Networks and Convolutional Neural Networks



What is an Artificial Neural Network (ANN)?

Inspired by the complex networks of the human brain, Artificial Neural Networks (ANNs) are advanced computer models designed to learn detailed patterns directly from data. They play a key role in modern artificial intelligence.



Brain-Inspired Design

Mimics the structure and function of interconnected biological neurons to process information.



Layered Structure

Composed of multiple layers of artificial neurons, transforming inputs to outputs through weighted connections.



Pattern Recognition

Excels at identifying underlying patterns and relationships within vast datasets.



Diverse Applications

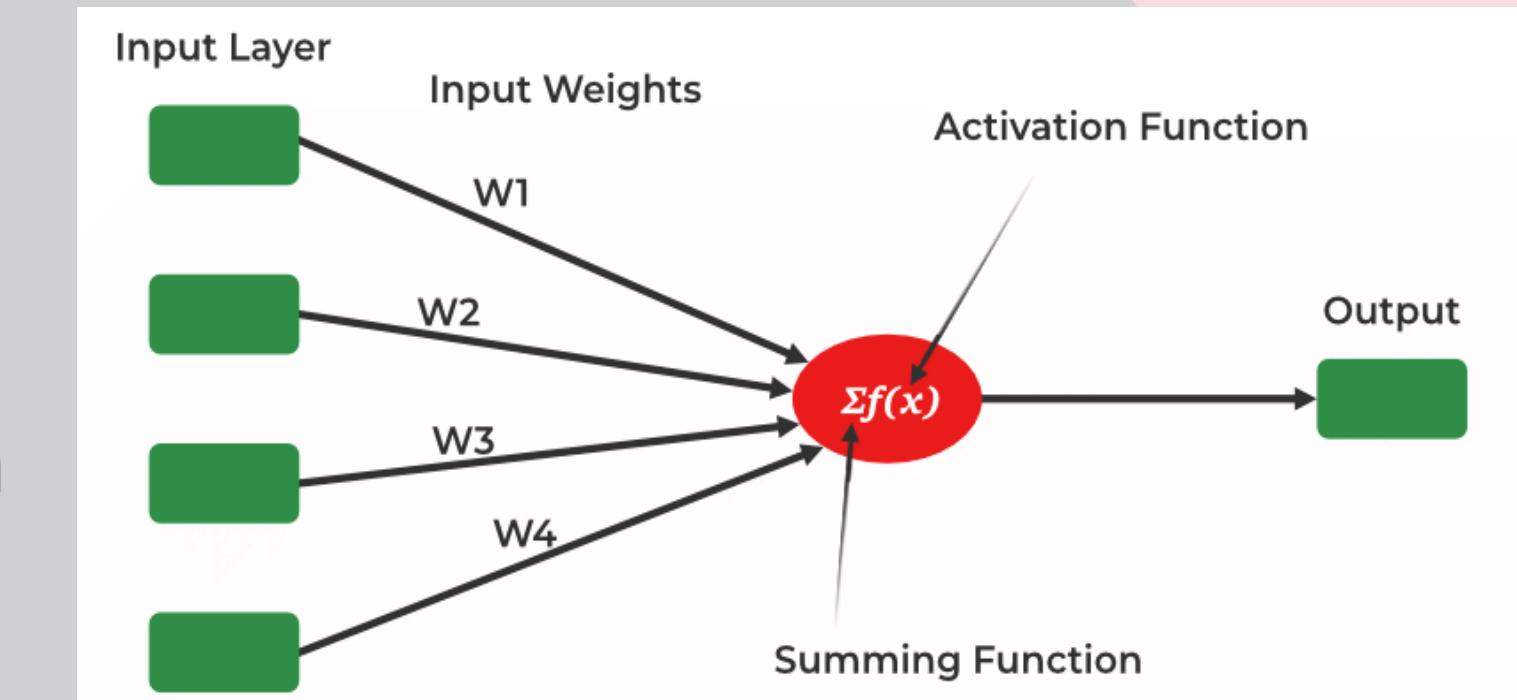
Widely applied in areas such as image recognition, natural language processing, and predictive analytics.



Single Layer Neural Network (SLNN)

A Single Layer Neural Network is an artificial neural network that has only one layer of trainable weights connecting the input layer directly to the output layer without any hidden layers.

- Consists of input nodes and output neurons
- No hidden layer is present
- Works on linear decision boundaries
- Uses a simple weighted sum and activation function
- Also known as Perceptron model



Working & Learning of SLNN

Working Principle:

1. Input values are multiplied with weights.
2. All weighted inputs are added : Net input = $\sum (w_i \times x_i) + \text{bias}$
3. The result is passed through an activation function to produce output.

Learning Rule (Perceptron Rule):

Weights are updated as:

$$w(\text{new}) = w(\text{old}) + \eta (\text{Target} - \text{Output}) \times \text{Input}$$

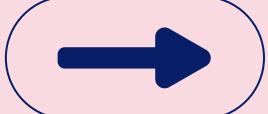
Where : η = Learning rate ; Target = Desired output

Limitations:

- Can solve only linearly separable problems
- Cannot solve XOR problem

Applications:

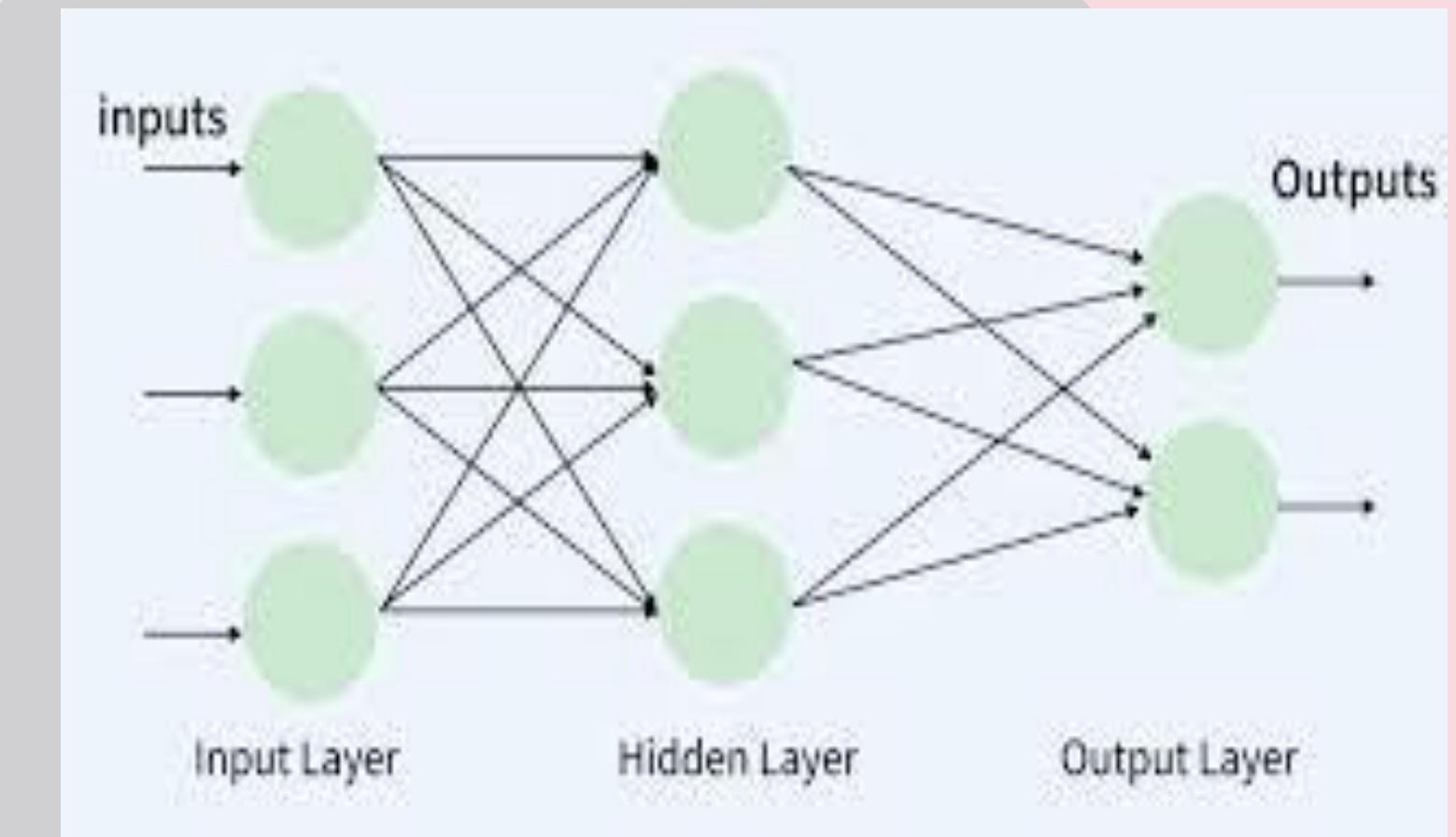
- Simple pattern classification
- Binary decision problems



Multilayer Perceptron (MLP)

A Multilayer Perceptron (MLP) is a type of feed-forward artificial neural network that consists of an input layer, one or more hidden layers, and an output layer, where neurons are connected using weighted links.

- Has at least one hidden layer
- Uses non-linear activation functions
- Capable of solving non-linearly separable problems
- Fully connected network



Input Layer

Hidden Layer(s)

Output Layer



Working & Learning of MLP

Working Principle:

1. Input signals are passed to the hidden layer neurons.
2. Each neuron performs weighted sum:
3. $\text{Net} = \sum (w_i \times x_i) + \text{bias}$
4. Output of each neuron is passed through an activation function (ReLU, Sigmoid, Tanh).
5. Final output is produced at the output layer.

Learning Rule (Back-propagation):

- MLP uses supervised learning.
- Error is calculated using a loss function.
- Error is propagated backward from output to hidden layers.
- Weights are updated using gradient descent.

Advantages:

- Can solve complex non-linear problems
- High accuracy

Applications:

- Image ; Speech ; Handwriting Recognition



Back Propagation Learning Algorithm

Backpropagation is a supervised learning algorithm used in multilayer neural networks that adjusts weights by propagating error backward from output layer to hidden layers.

- Based on gradient descent
- Uses chain rule of differentiation
- Minimizes loss/error function

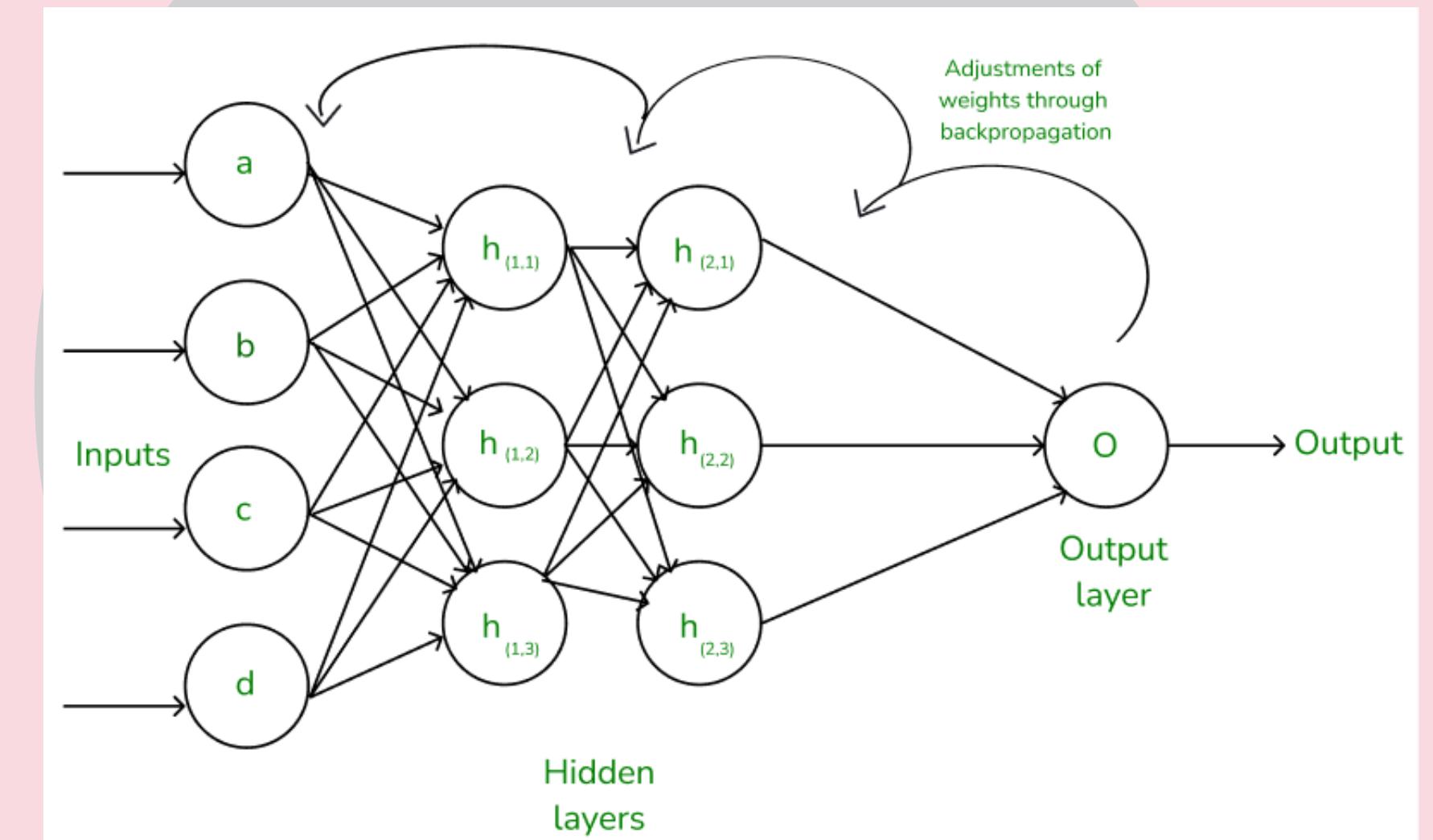
Error Formula :

$$E = \frac{1}{2} (\text{Target} - \text{Output})^2$$

- Forward pass: calculate outputs.
- Compute error at output layer.
- Backward pass: calculate gradients.
- Update weights : $w(\text{new}) = w(\text{old}) - \eta (\partial E / \partial w)$

Advantages: High accuracy

Limitation: Slow learning in large networks



Functional Link Artificial Neural Network (FLANN)

FLANN is a single-layer neural network that improves learning by expanding input features using mathematical functions without hidden layers.

Functional Expansion Examples :

- Trigonometric (\sin , \cos)
- Polynomial (x^2 , x^3)
- Exponential

Working :

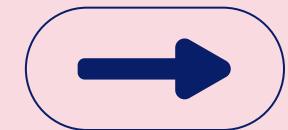
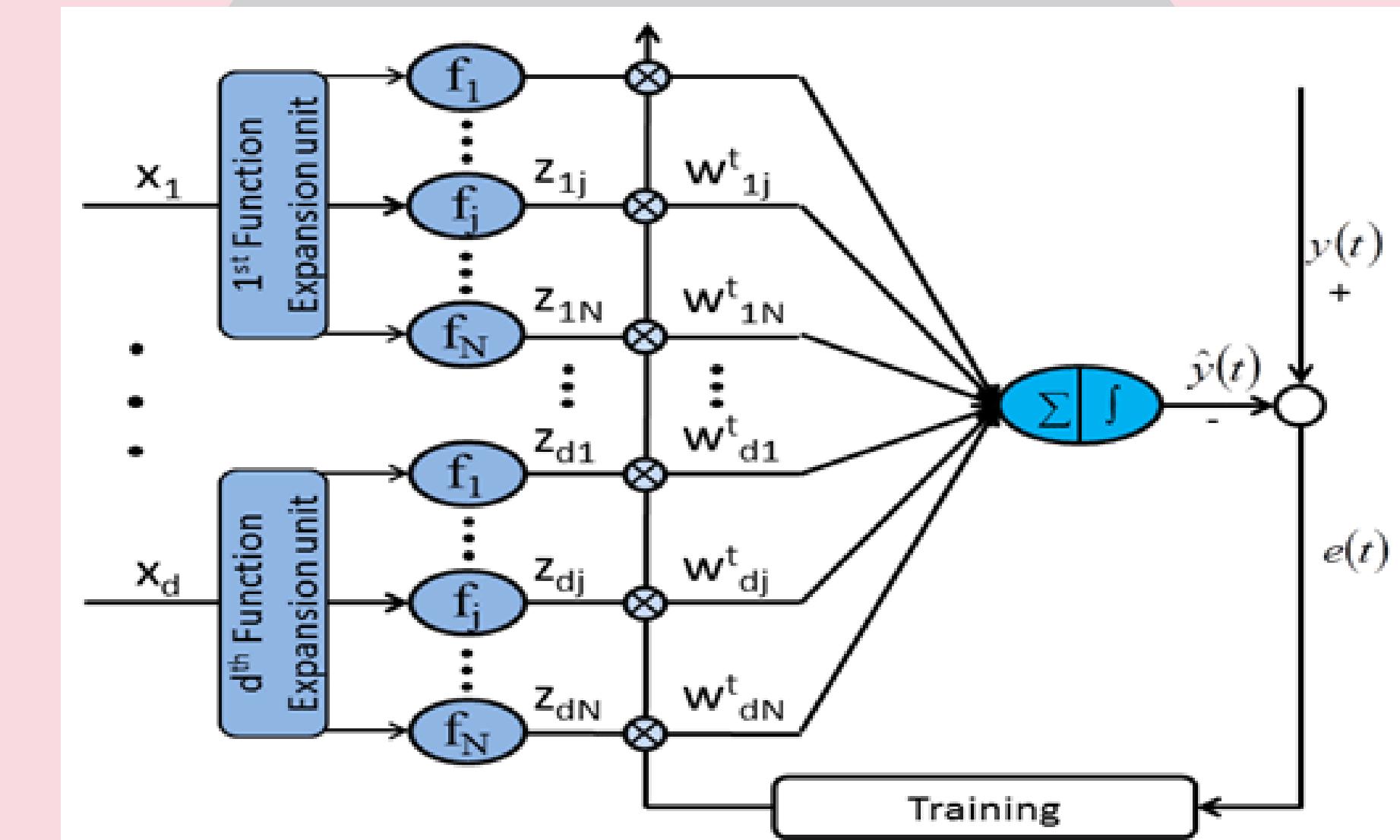
- Input expansion using basis functions
- Weighted sum
- Activation \rightarrow Output

Advantages:

- Faster Learning than MLP
- Less computational cost

Application :

- Signal Processing
- Pattern Recognition



Radial Basis Function Network (RBFN)

RBFN is a neural network that uses radial basis functions (Gaussian) as activation functions in the hidden layer.

Working Principle:

- Measures distance between input and center
- Neuron fires based on closeness

Structure :

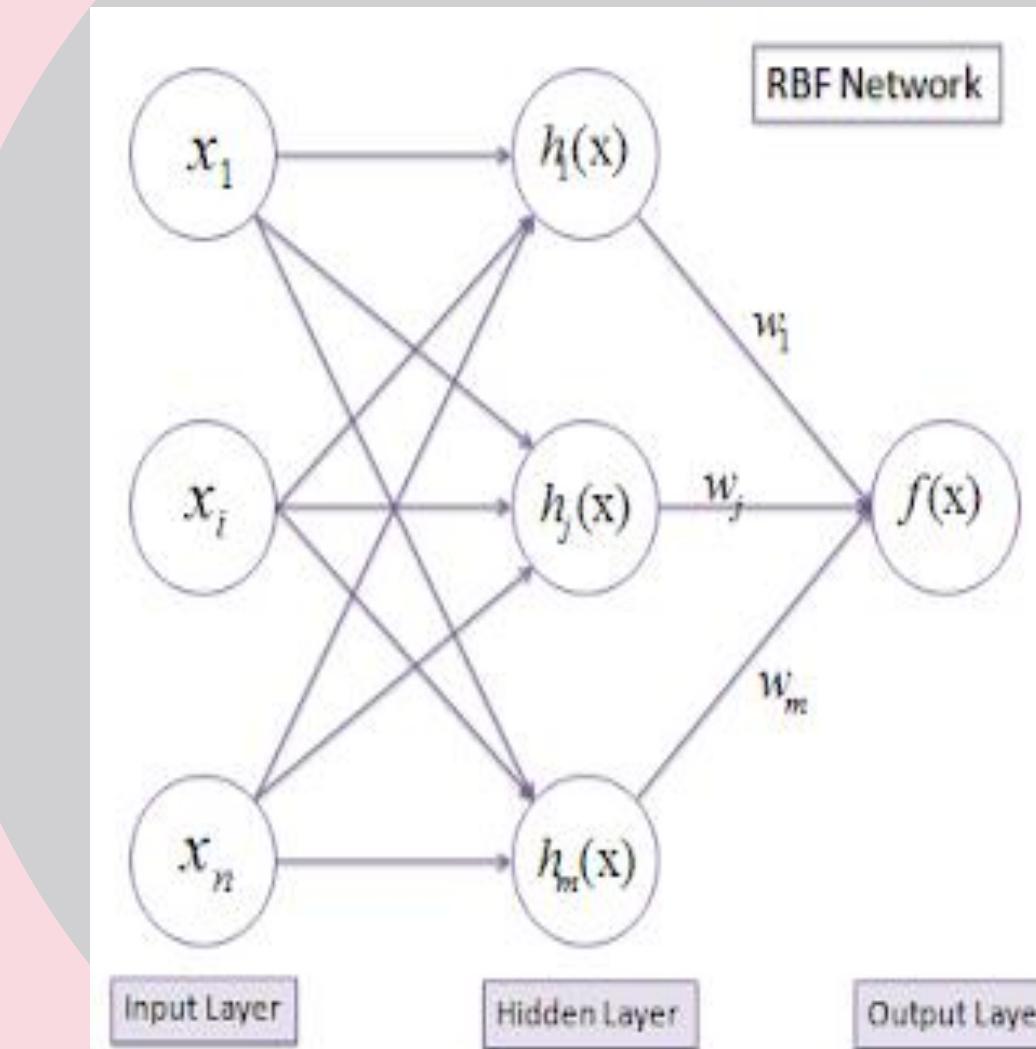
Input Layer → RBF Hidden Layer → Output Layer

Advantages:

- Fast Training
- Good for function approximation

Applications:

- Time series prediction
- Control Systems



$$f(x) = \sum_{j=1}^m w_j h_j(x)$$

$$h(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right)$$



Activation Functions

Activation functions introduce non-linearity into neural networks and decide whether a neuron should be activated or not.

Purpose :

- Control neuron output
- Enable complex pattern learning

Types of Activation Functions

FUNCTION	FORMULA	RANGE
Sigmoid	$1/(1+e^{-x})$	0 to 1
Tanh	$\tanh(x)$	-1 to 1
ReLU	$\max(0, x)$	0 to ∞
Softmax	$e^{x_i}/\sum e^{x_i}$	Probabilities



Recurrent Neural Networks (RNN)

RNN is a neural network designed to handle sequential data by having feedback loops that store past information.

Why RNN?

- Remembers previous inputs
- Used for time-dependent data

Features :

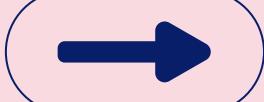
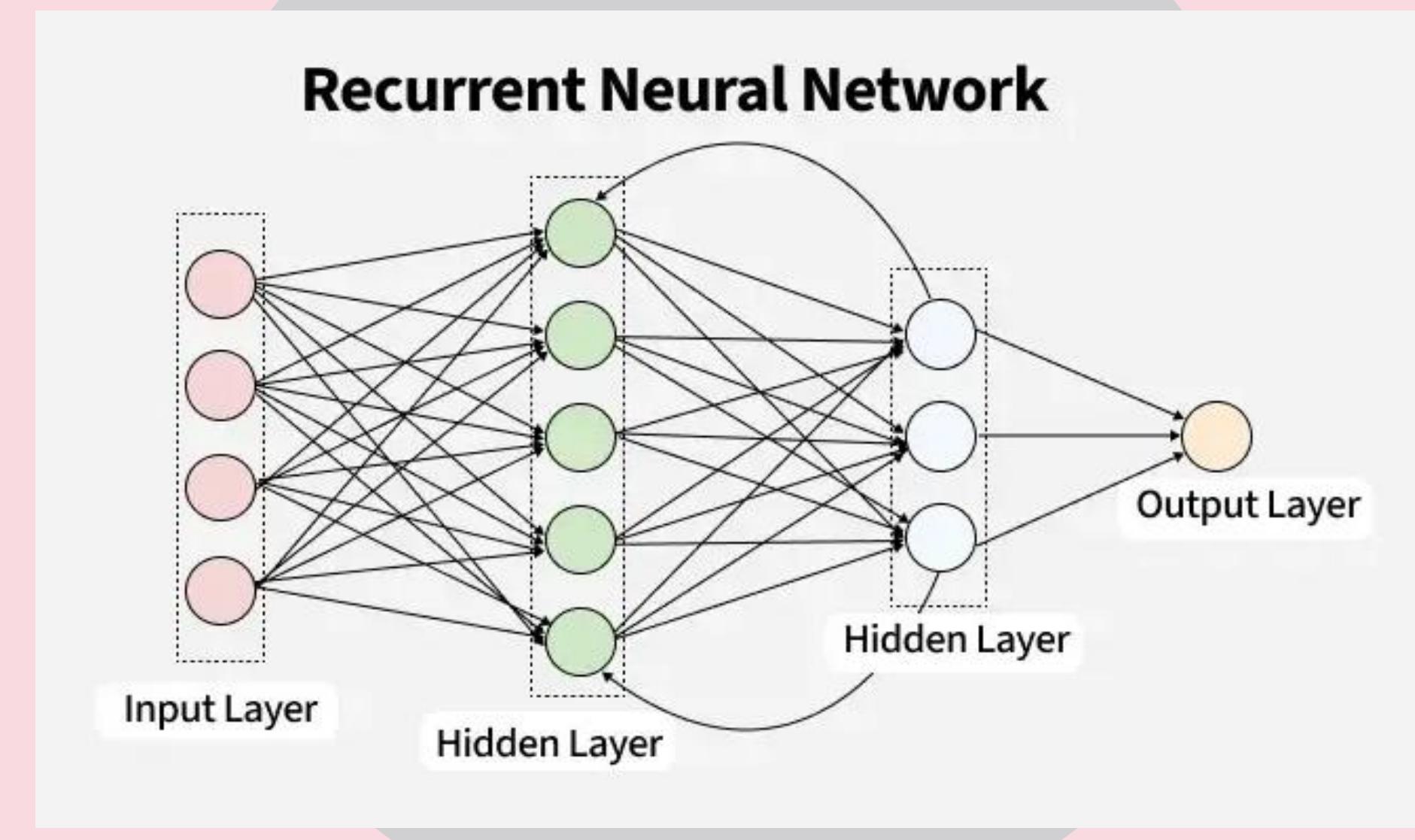
- ❑ Has internal memory (hidden state)
- ❑ Shares weights across time steps

Types :

1. Simple RNN
2. LSTM
3. GRU

Applications:

- Speech recognition
- Language translation



Convolutional Neural Networks (CNN)

CNN is a deep neural network specially designed for image and spatial data processing.

Main Layers:

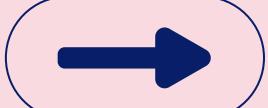
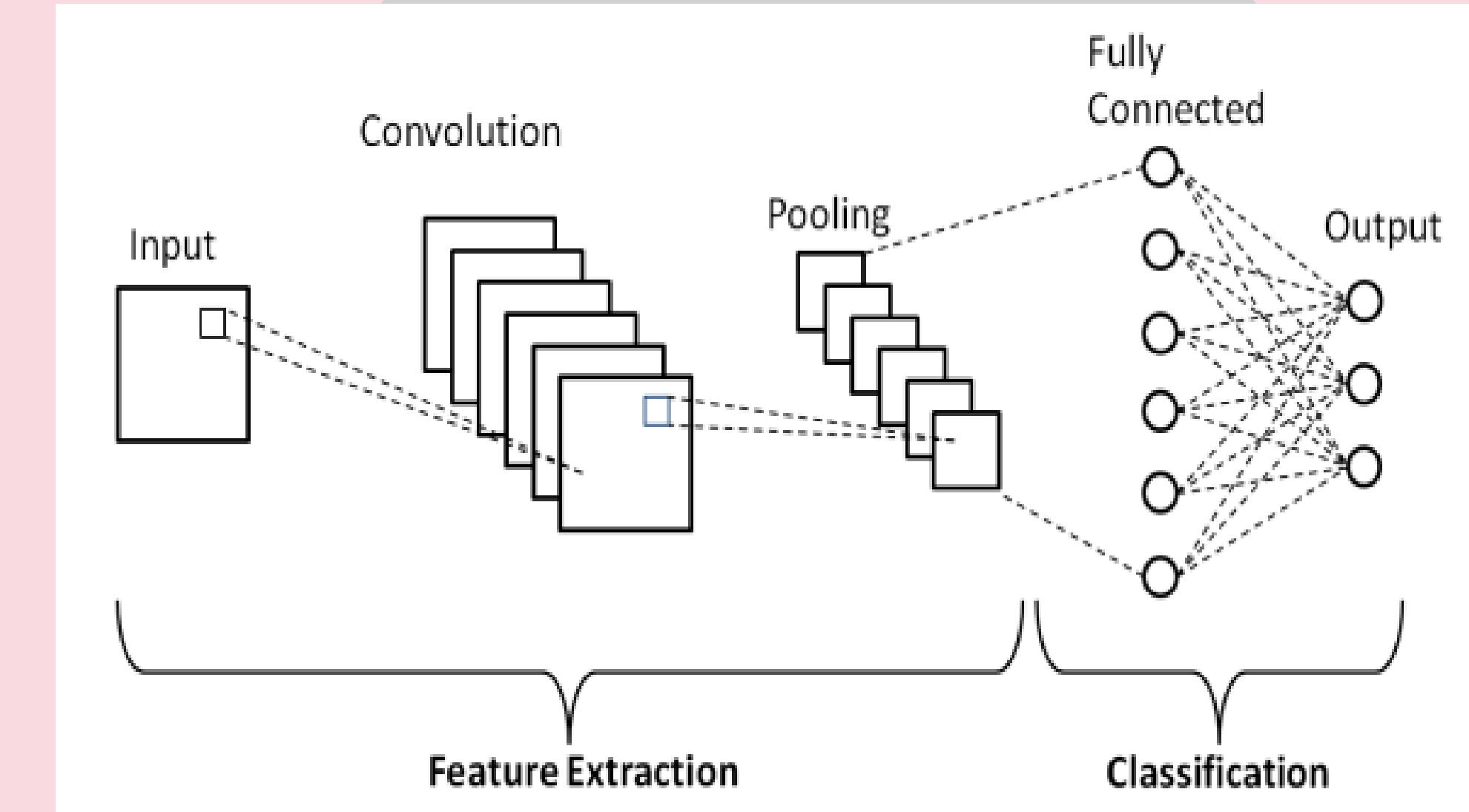
- Convolution layer
- Pooling layer
- Fully connected layer

Working:

1. Convolution extracts features
2. Pooling reduces size
3. Fully connected layer classifies

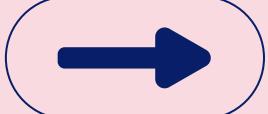
Applications:

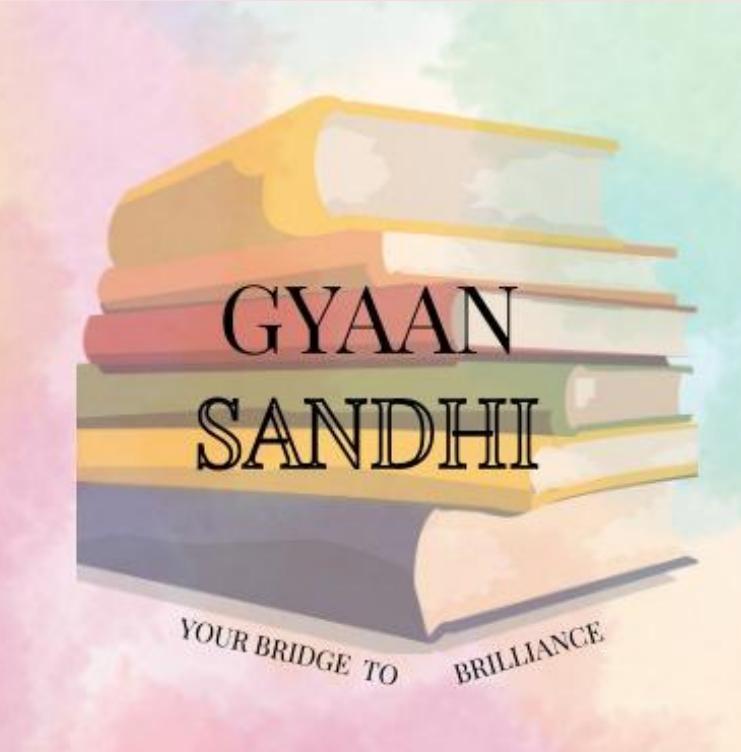
- Image recognition
- Face detection
- Medical image analysis



Difference Between CNN and RNN

Feature	CNN (Convolutional Neural Network)	RNN (Recurrent Neural Network)
Data Type	Works on spatial data (images, videos)	Works on sequential data (text, speech, time series)
Architecture	Uses convolution and pooling layers	Uses recurrent (loop) connections
Memory	No memory of previous inputs	Has memory using hidden states
Key Operation	Convolution (feature extraction)	Recurrence (information feedback)
Weight Sharing	Shares weights spatially	Shares weights over time steps
Input Handling	Processes whole input at once	Processes input step-by-step (sequence)
Main Layers	Convolution, Pooling, Fully Connected	Input, Hidden (recurrent), Output
Training Method	Backpropagation	Backpropagation Through Time (BPTT)
Best Suited For	Image recognition, object detection	Speech recognition, text prediction
Examples	Image classification, face detection	Language translation, chatbots





THANK

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