

Fast cancer Detection using Deep learning

Prepared by:

K. Chandrika

Jyothi

Outline

- What's Breast cancer
- Abstract and introduction
- Modules and architecture diagram
- Mammography
- Classes: benign and malignant
- Neural network
- Identifying breast cancer
- Support vector machine

Objectives

- In this presentation you obtain main information about breast cancer and how we analyse, detect breast types
- Explain all dataset types
- Explain classes in breast cancer
- Define main parts of CNN model for training data

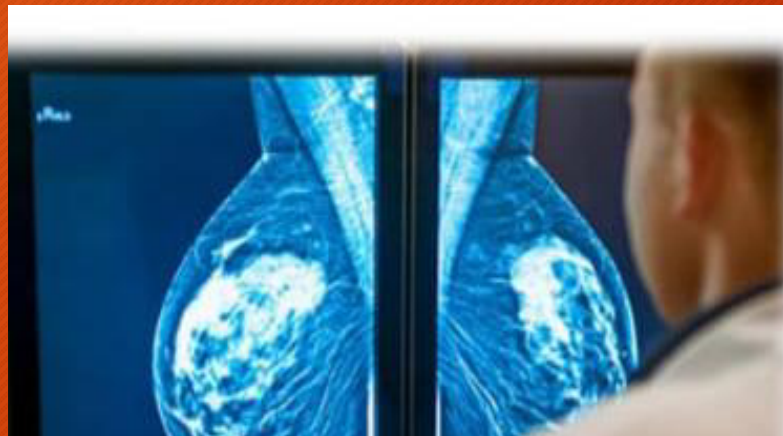
Aim

- Classify features extracted from mammogram FNA images as malignant or benign based on
- extracted features using Support Vector Machines (SVMs).



Introduction to Breast cancer

- Breast cancer is the most common Cancer type diagnosed in women worldwide.while breast cancer can occur in both men and women,it is by far more prevalent in women.
- Breast cancer incidence in women in the United States is 1 in 8 (about 13%) women have a 3% chance of breast cancer using their death.
- Feature extraction helps discriminate between benign and malignant tumors



Abstract

- Researchers have developed computer- aided systems for efficiency diagnosis of breast cancer from histopathological microscopic images.
- It detect the tumor cells automatically using advanced image processing techniques.
- It also recognise the tumor shape and position in MRI image using classification method.
- The results displayed whether it is benign or malignant.

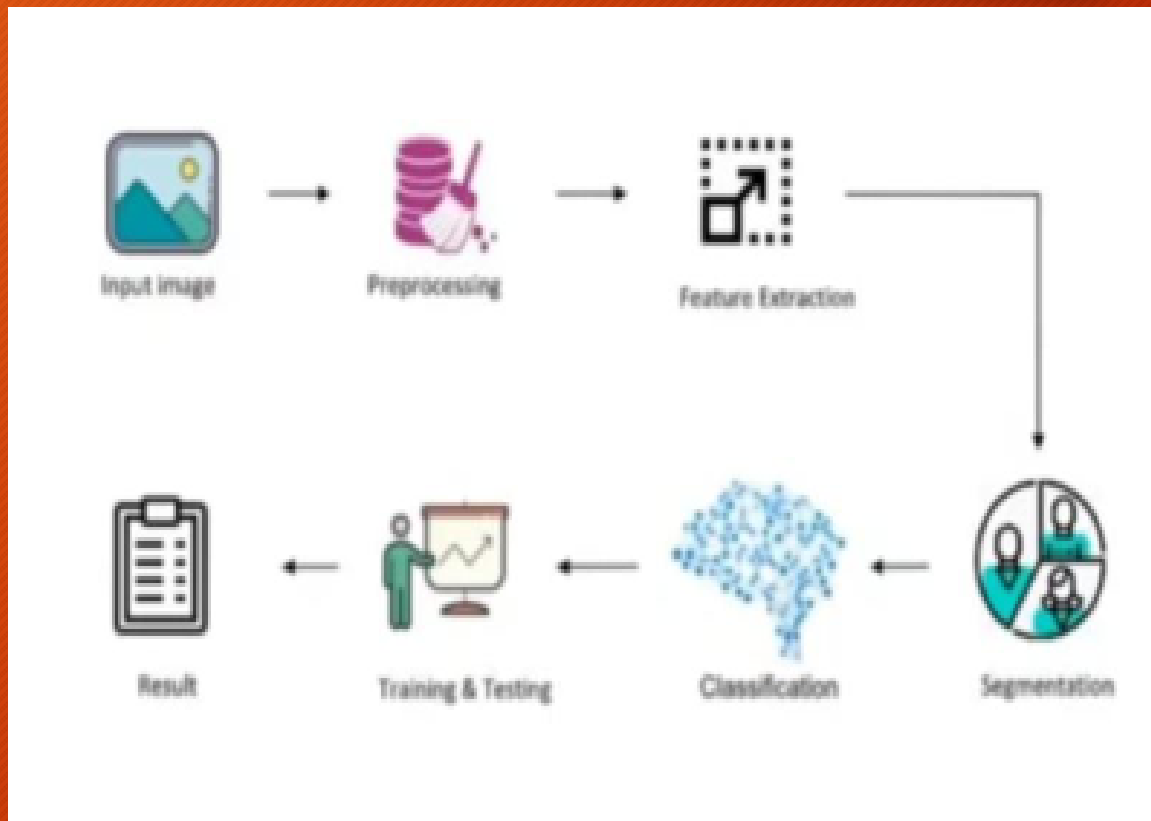
MamMography

- Mammography is the recommended imaging modality for breast cancer screening
- It is more useful as an early detection tool before the appearance of the physical symptoms.



Modules and architecture diagram

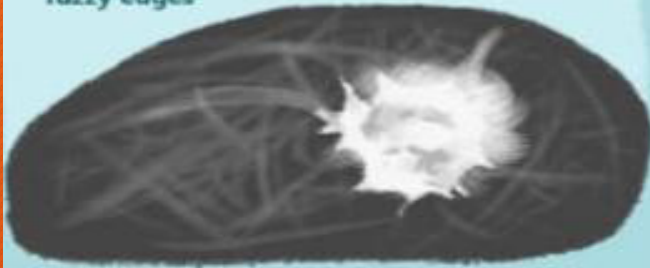
- Preprocessing
- Segmentation
- Masked image
- Feature extraction
- Classification



Identifying breast cancer

Identifying Breast Cancer

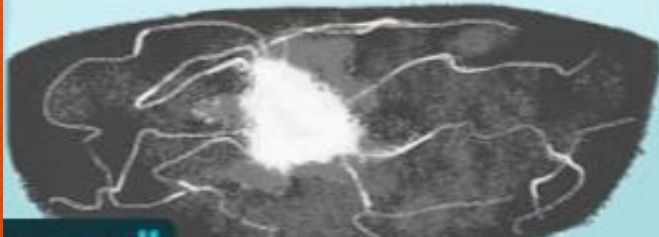
Mammogram: Cancerous mass may appear as a bright and irregular image with spiky or fuzzy edges



Ultrasound: Cancerous mass appears darker, indicating it's solid. It may also have spiky or irregular edges

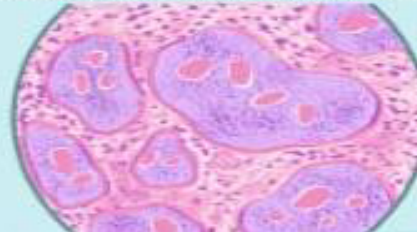


MRI: Contrast agent causes cancerous mass - or outside of mass - to brighten, then fade. Irregular or spiky borders are common



Biopsy: Under microscope, cancer cells may:

- appear clustered
- have irregular, large, or additional nuclei
- be invading blood vessels or lymphatic vessels



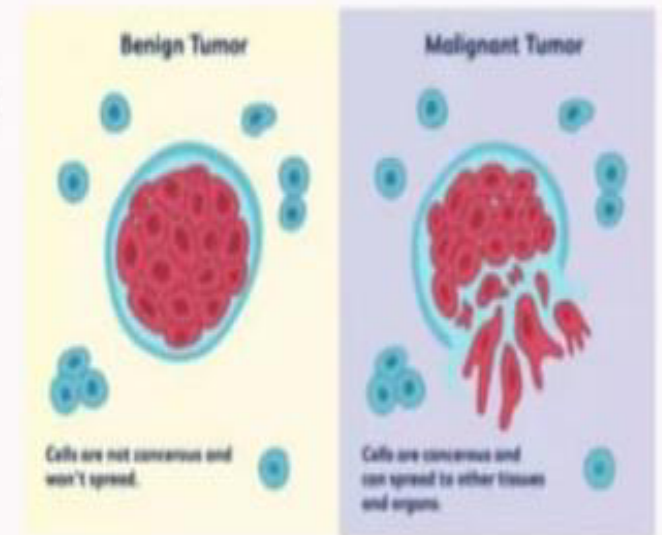
Classes:

- Benign tumor: it has distinct smooth, regular borders. A benign tumor can become larger, but will not invade nearby tissue or spread to other parts of your body. These are non-cancerous tumors.
- Malignant tumor: It has irregular borders and grows faster than a benign tumor. It can also spread to other parts of your body. These are cancerous tumors.

CLASSES:

Malignant Tumor:
Cancerous

Benign Tumor:
Not-Cancerous

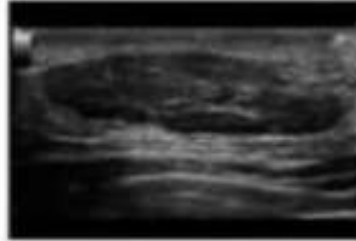


Benign and malignant tumors

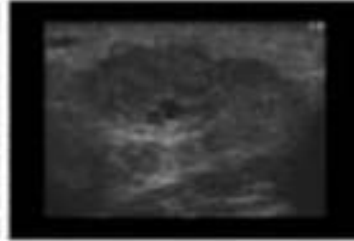
Benign



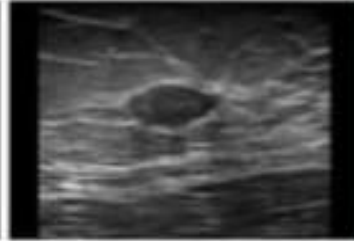
Infected cysts



Lipomas

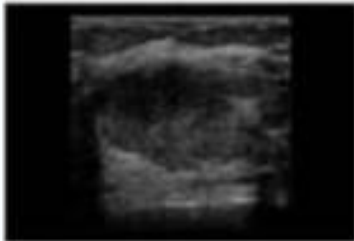


Inflammation

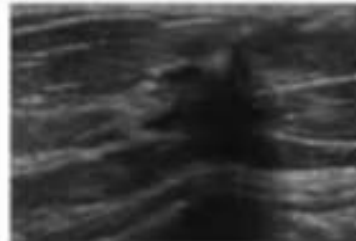


Fibro adenomas

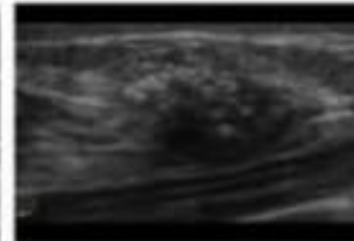
Malignant



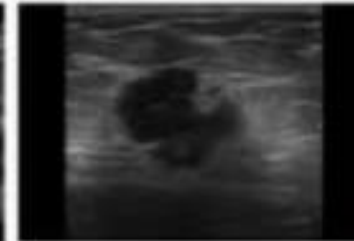
Metastases



Spreading bilateral



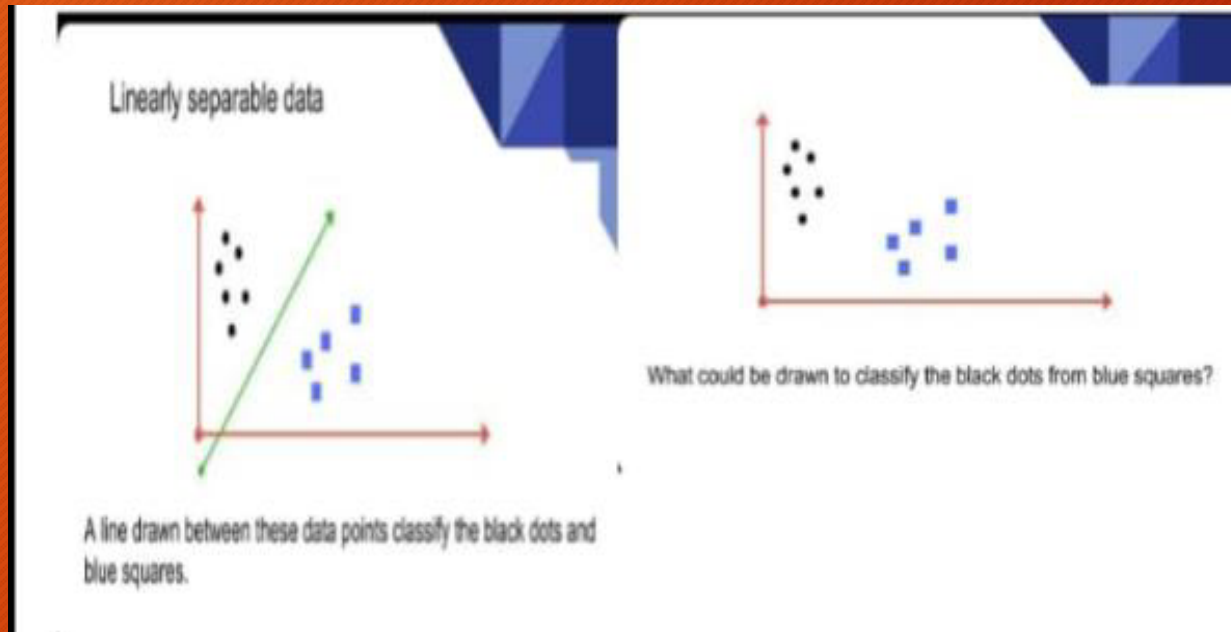
Carcinoma in situ



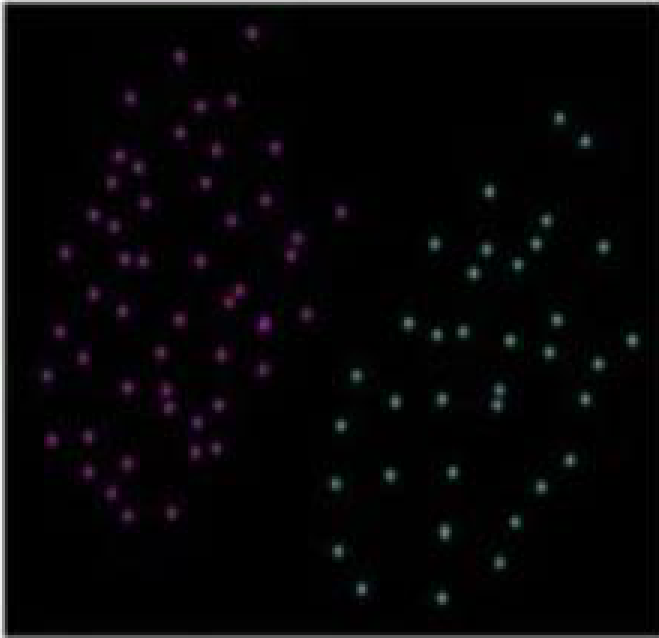
Microcalcification

Support vector machine

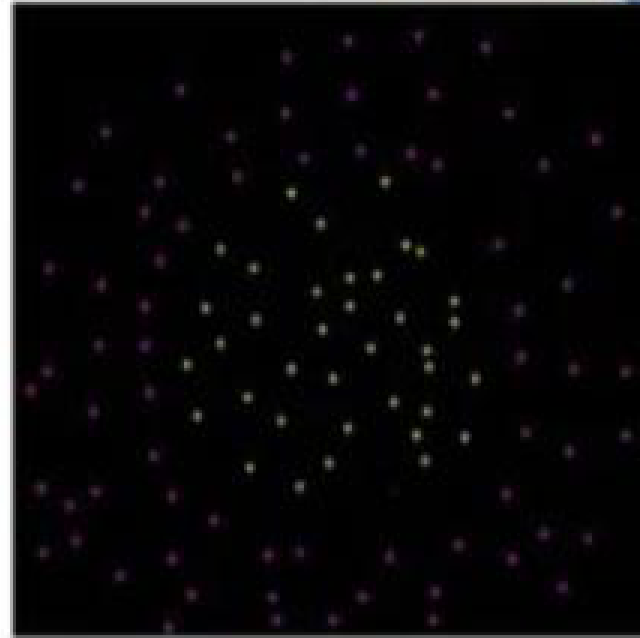
- A svm is a discriminative classifier which intakes training data, the algorithm outputs an optimal hyperplane which categorizes new examples.,



Linear vs nonlinear separable data



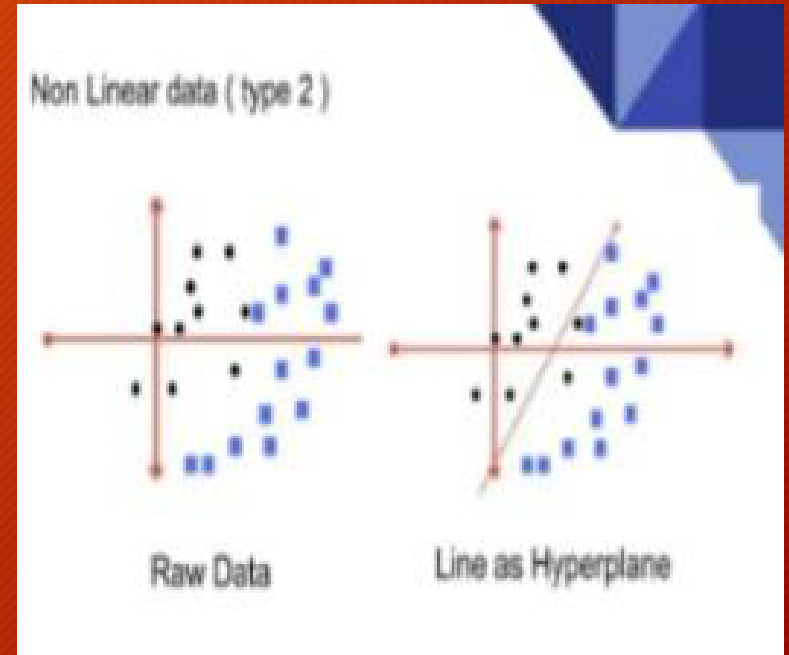
Linearly separable data



Non linearly separable data

Non linear data

- For the previous data the line, if user as a hyperplane
- Two black dots also fall in category of blue squares
- Data separation is not perfect
- It tolerates some outliers in the classification



Various kernels available

1. Linear kernel
2. Non linear kernel
3. Radial basis function
4. Sigmoid
5. Polynomial
6. Exponential

Mathematical expression

$$x = (x_1, x_2, x_3); y = (y_1, y_2, y_3)$$

$$f(x) = (x_1x_1, x_1x_2, x_1x_3, x_2x_1, x_2x_2, x_2x_3, x_3x_1, x_3x_2, x_3x_3)$$

$$f(y) = (y_1y_1, y_1y_2, y_1y_3, y_2y_1, y_2y_2, y_2y_3, y_3y_1, y_3y_2, y_3y_3)$$

$$K(x, y) = (\langle x, y \rangle)^2$$

$$x = (1, 2, 3)$$

$$y = (4, 5, 6)$$

$$f(x) = (1, 2, 3, 2, 4, 6, 3, 6, 9)$$

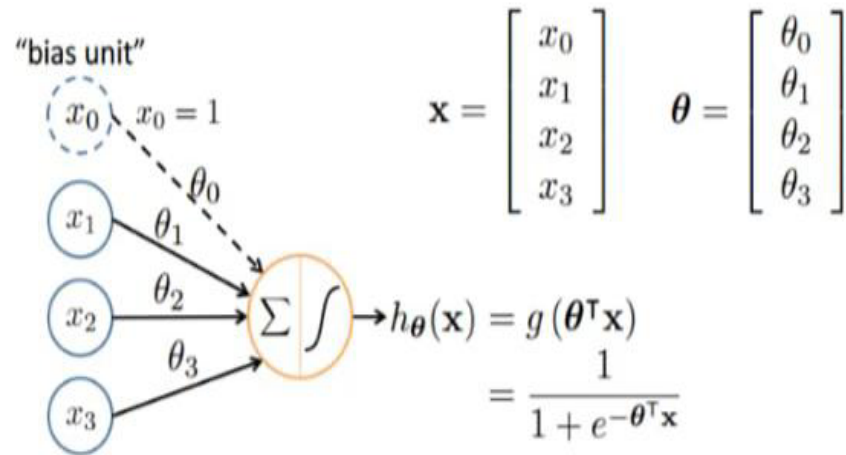
$$f(y) = (16, 20, 24, 20, 25, 30, 24, 30, 36)$$

$$\langle f(x), f(y) \rangle = 16 + 40 + 72 + 40 + 100 + 180 + 72 + 180 + 324 = 1024$$

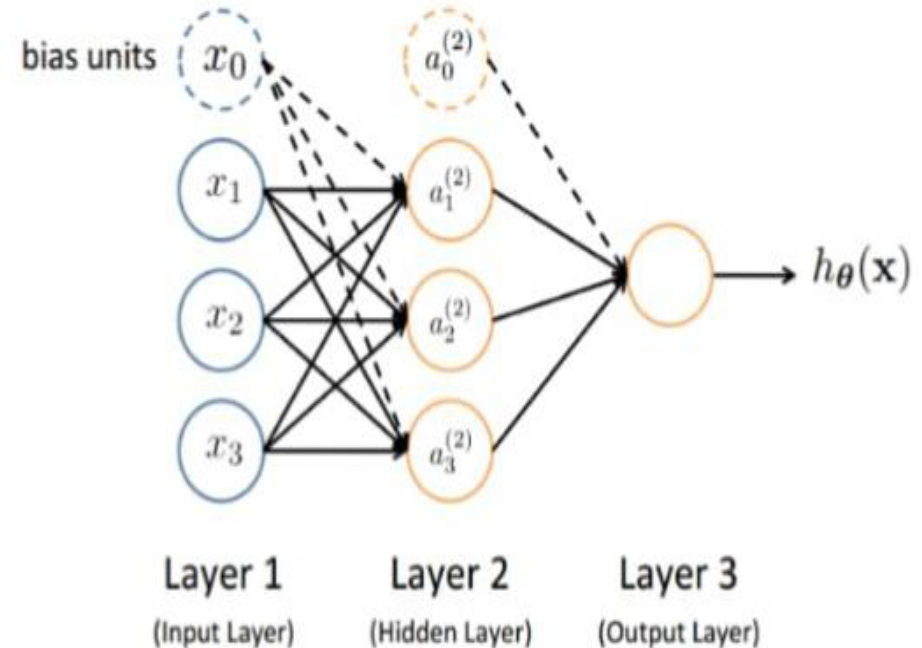
$$K(x, y) = (4 + 10 + 18)^2 = 1024 \text{ ----> Kernel function}$$

Neural network (feed forward)

Neural Network

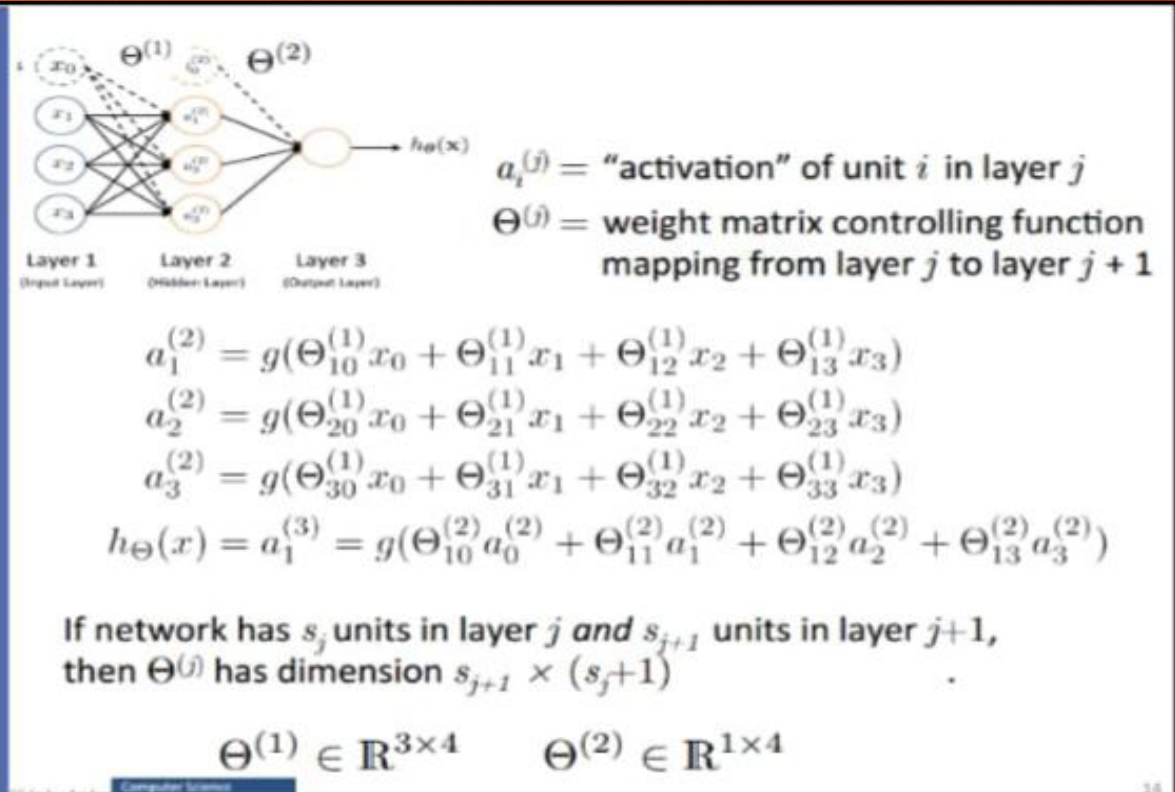


Sigmoid (logistic) activation function: $g(z) = \frac{1}{1 + e^{-z}}$



Feed –forward process

- ❖ Input layer units are features (in NLP, e.g., words)
 - ❖ Usually, one-hot vector or word embedding
- ❖ Working forward through the network, the **input function** is applied to compute the input value
 - ❖ E.g., weighted sum of the input
- ❖ The **activation function** transforms this input function into a final value
 - ❖ Typically a **nonlinear** function (e.g, **sigmoid**)



Vector representation

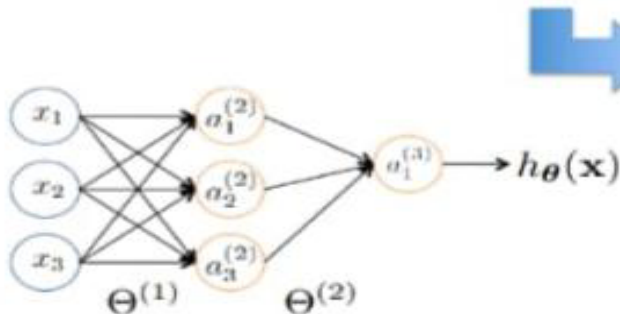
Vector Representation

$$a_1^{(2)} = g \left(\Theta_{10}^{(1)} x_0 + \Theta_{11}^{(1)} x_1 + \Theta_{12}^{(1)} x_2 + \Theta_{13}^{(1)} x_3 \right) = g \left(z_1^{(2)} \right)$$

$$a_2^{(2)} = g \left(\Theta_{20}^{(1)} x_0 + \Theta_{21}^{(1)} x_1 + \Theta_{22}^{(1)} x_2 + \Theta_{23}^{(1)} x_3 \right) = g \left(z_2^{(2)} \right)$$

$$a_3^{(2)} = g \left(\Theta_{30}^{(1)} x_0 + \Theta_{31}^{(1)} x_1 + \Theta_{32}^{(1)} x_2 + \Theta_{33}^{(1)} x_3 \right) = g \left(z_3^{(2)} \right)$$

$$h_{\Theta}(\mathbf{x}) = g \left(\Theta_{10}^{(2)} a_0^{(2)} + \Theta_{11}^{(2)} a_1^{(2)} + \Theta_{12}^{(2)} a_2^{(2)} + \Theta_{13}^{(2)} a_3^{(2)} \right) = g \left(z_1^{(3)} \right)$$



Feed-Forward Steps:

$$\mathbf{z}^{(2)} = \Theta^{(1)} \mathbf{x}$$

$$\mathbf{a}^{(2)} = g(\mathbf{z}^{(2)})$$

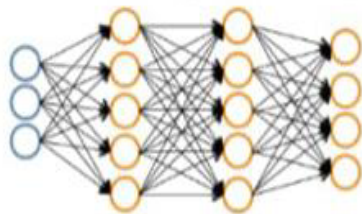
$$\text{Add } a_0^{(2)} = 1$$

$$\mathbf{z}^{(3)} = \Theta^{(2)} \mathbf{a}^{(2)}$$

$$h_{\Theta}(\mathbf{x}) = \mathbf{a}^{(3)} = g(\mathbf{z}^{(3)})$$

Extend to multi class

Can extend to multi-class



$$h_{\theta}(\mathbf{x}) \in \mathbb{R}^K$$

We want:

$$h_{\theta}(\mathbf{x}) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

when pedestrian

$$h_{\theta}(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

when car

$$h_{\theta}(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

when motorcycle

$$h_{\theta}(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

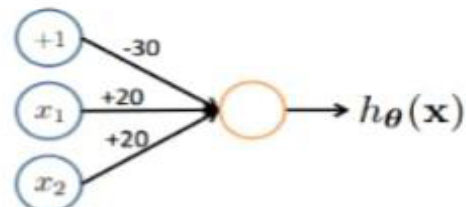
when truck

Why staged predictions?

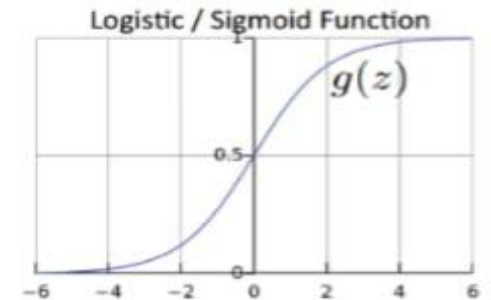
Simple example: AND

$$x_1, x_2 \in \{0, 1\}$$

$$y = x_1 \text{ AND } x_2$$

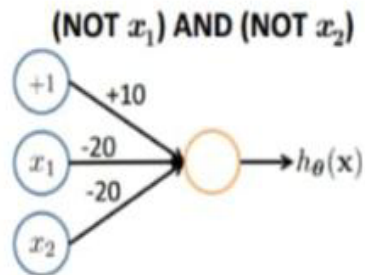
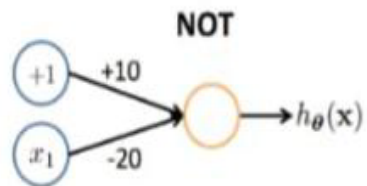
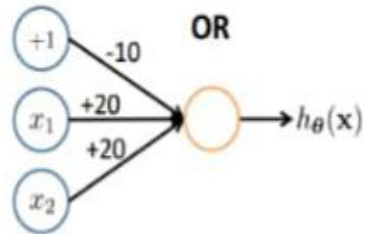
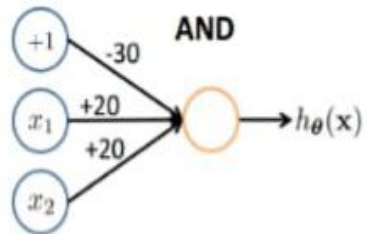


$$h_{\theta}(\mathbf{x}) = g(-30 + 20x_1 + 20x_2)$$

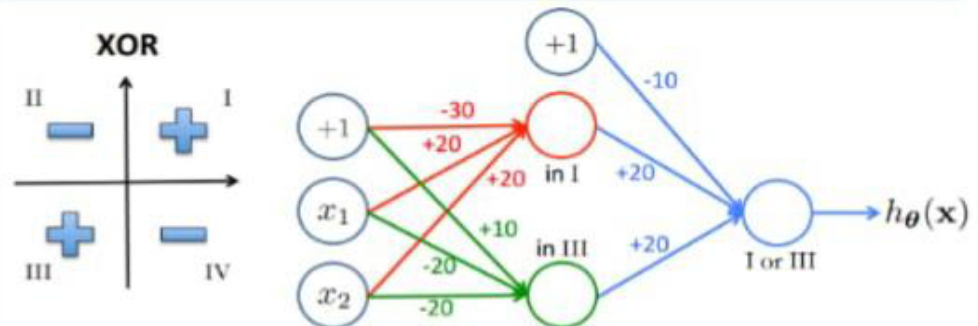
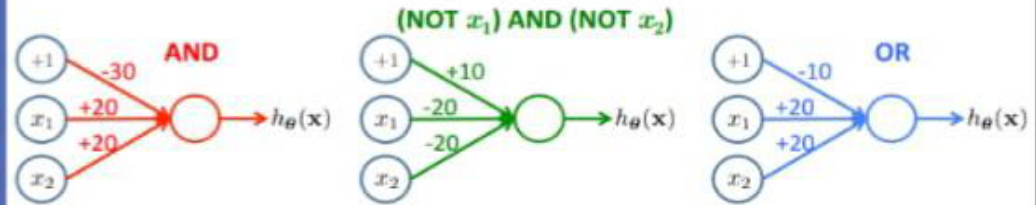


x_1	x_2	$h_{\theta}(\mathbf{x})$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

Combining representation to create nonlinear functions



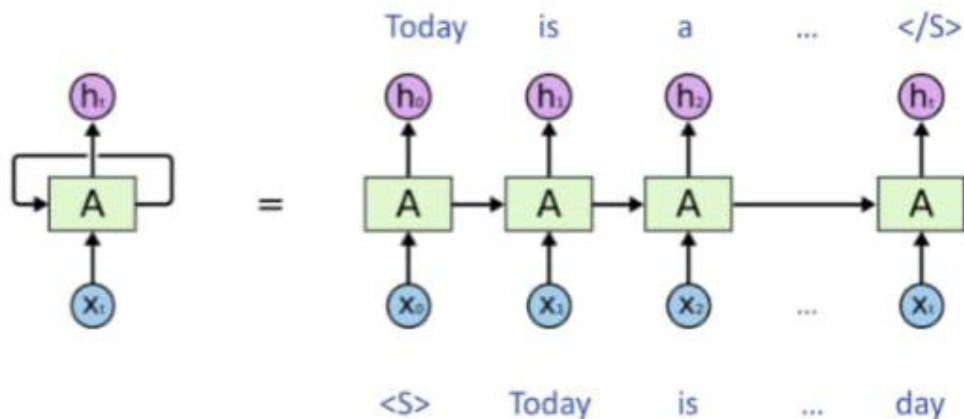
Combining Representations to Create Non-Linear Functions



Recurrent neural networks

How to deal with input with variant size?

❖ Use same parameters

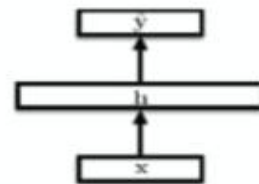


Recurrent Neural Networks

Feed-forward NN

$$\mathbf{h} = g(\mathbf{V}\mathbf{x} + \mathbf{c})$$

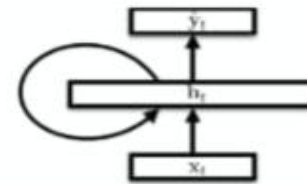
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h} + \mathbf{b}$$



Recurrent NN

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$

$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$



Conclusion

CONCLUSION

- The most common cause of cancer related to death in women.
- Early detection and screening is vital.
- Breast self-examination is important but it should not substituted for screening tests.
- Maintain a healthy weight, add exercise into our routine.
- Limit alcohol intake and non-smoking.

