

Deep Learning



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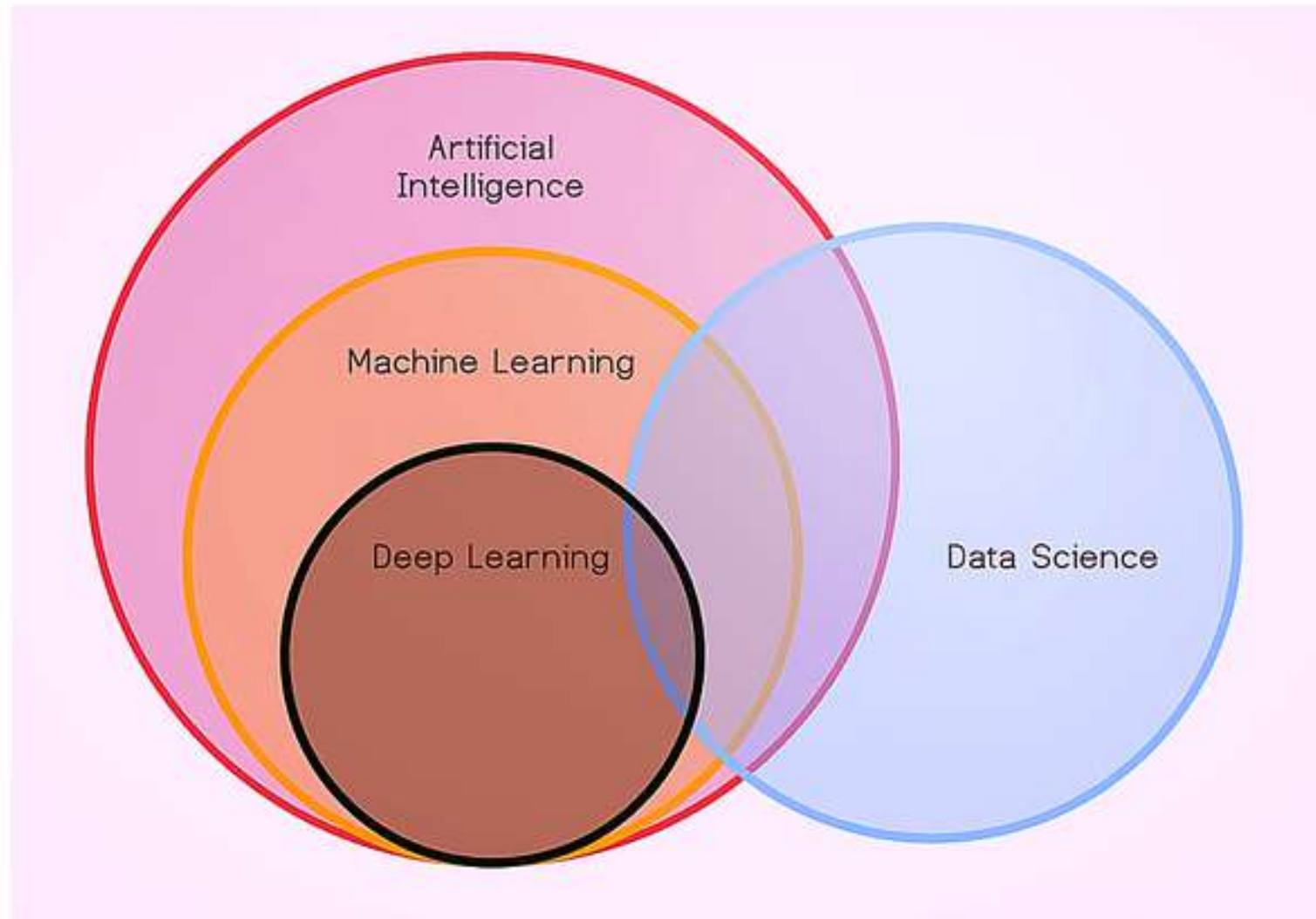
Institut Teknologi
Telkom
Purwokerto



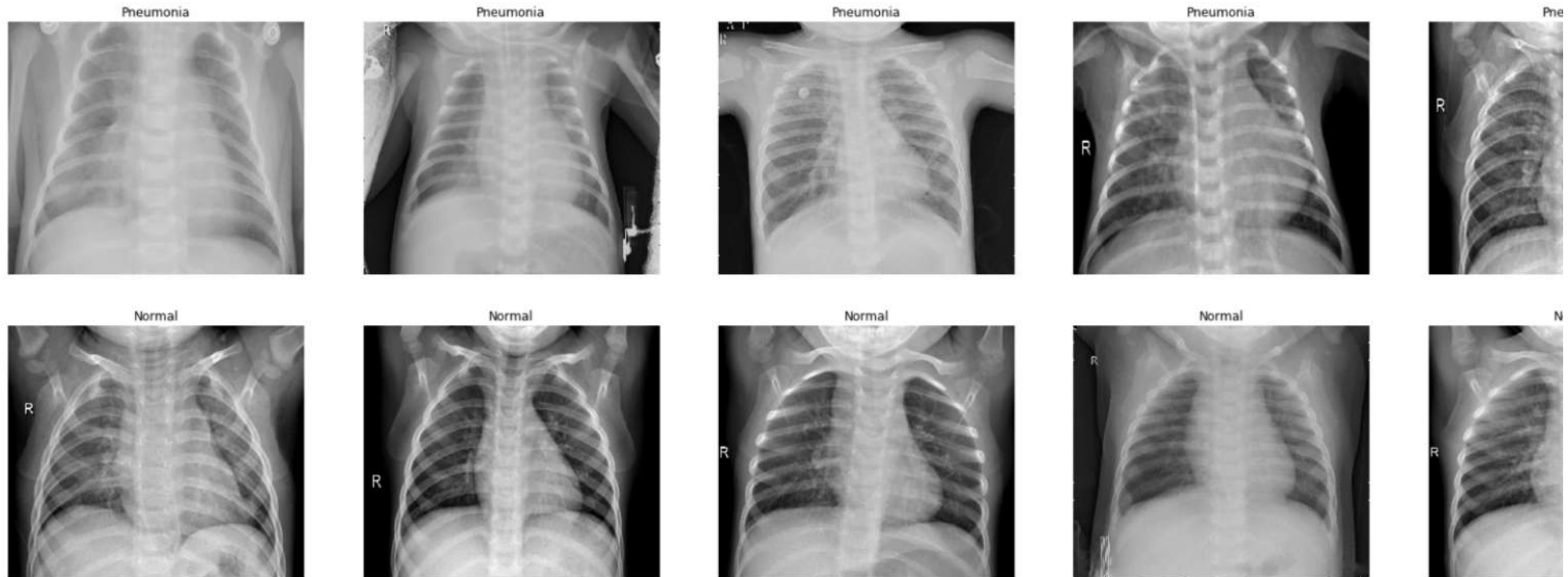
SAINS DATA



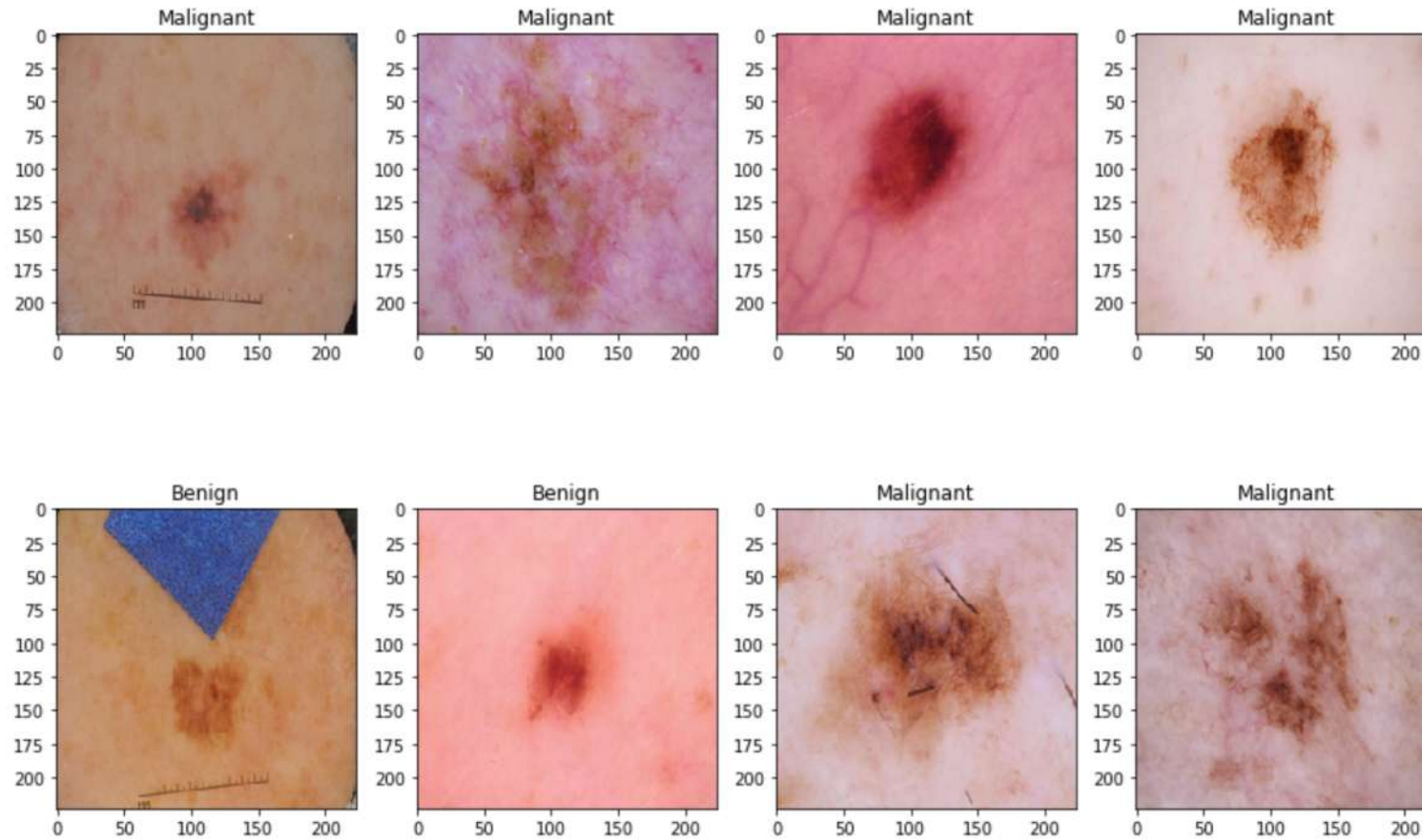
Artificial Intelligence



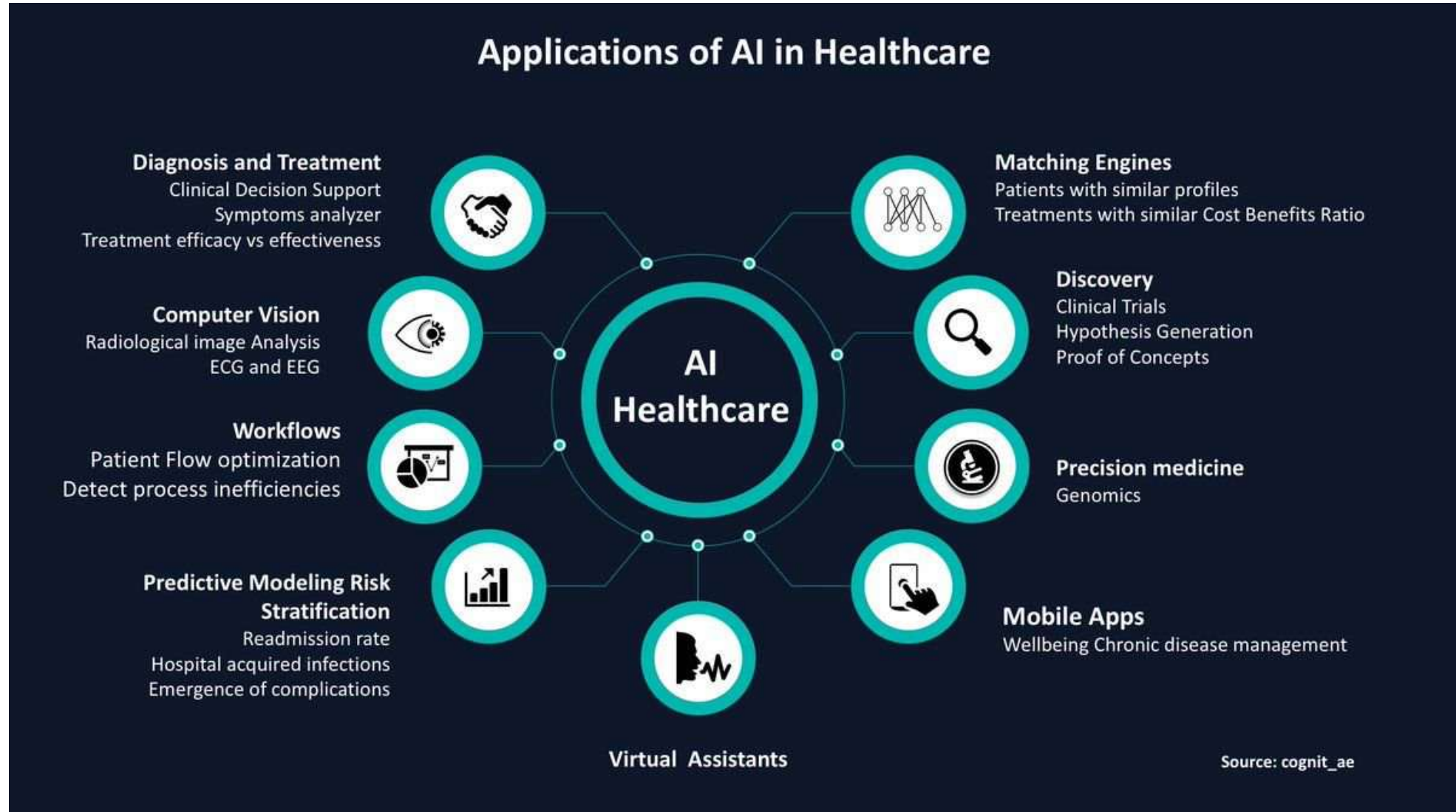
AI in Healthcare: Detect Pneumonia



AI in Healthcare: Skin Cancer Detection



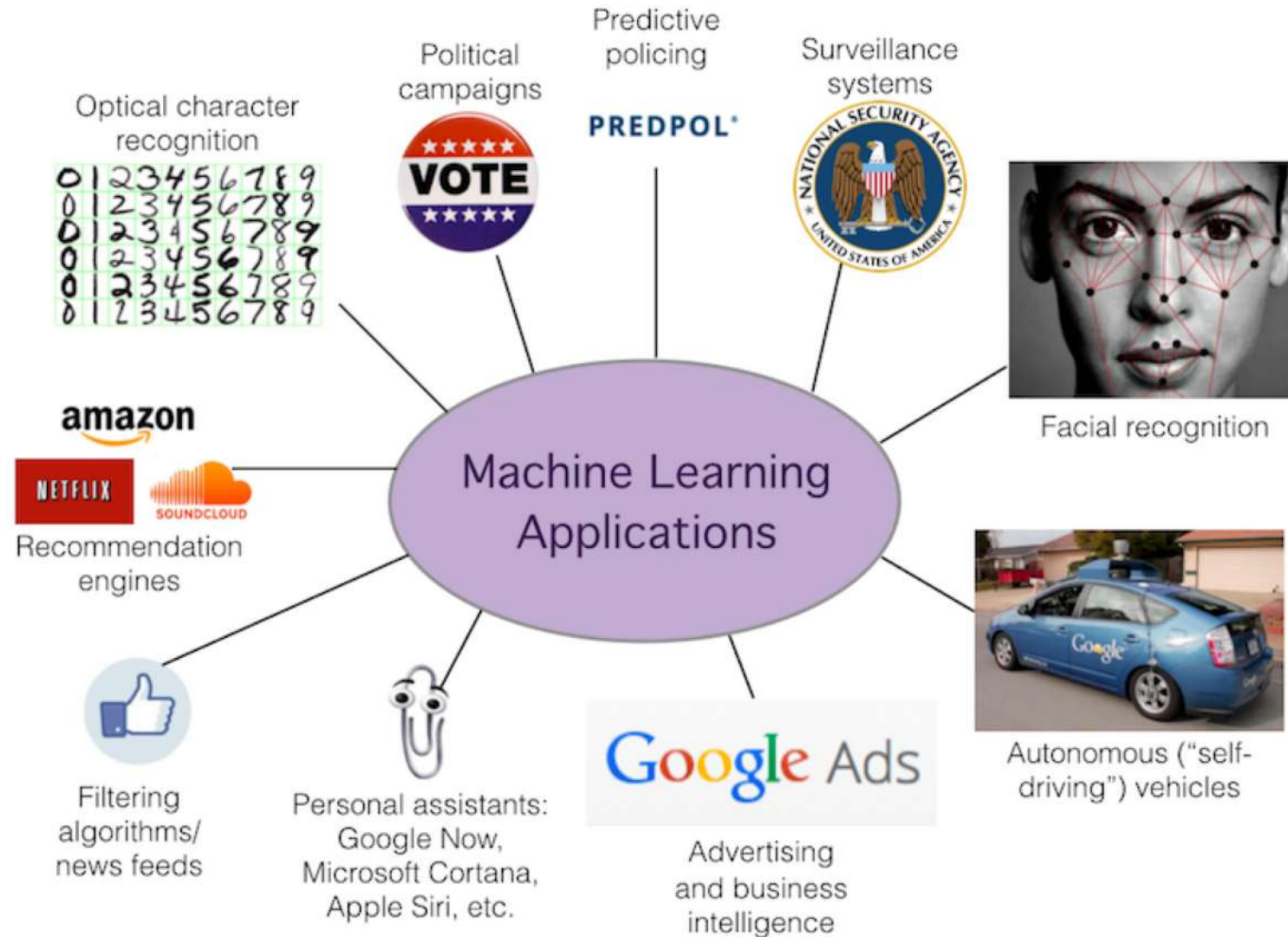
AI in Healthcare



We Focus on Machine Learning

- Subset dari Artificial Intelligence
- Konsep Machine Learning: **Performance, Tasks** dan **Experience**

Machine Learning Application

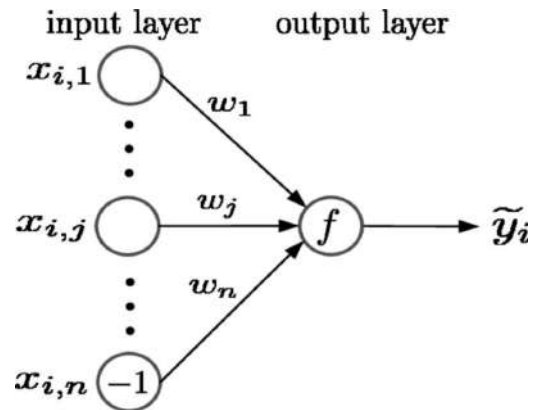


We Need Data!

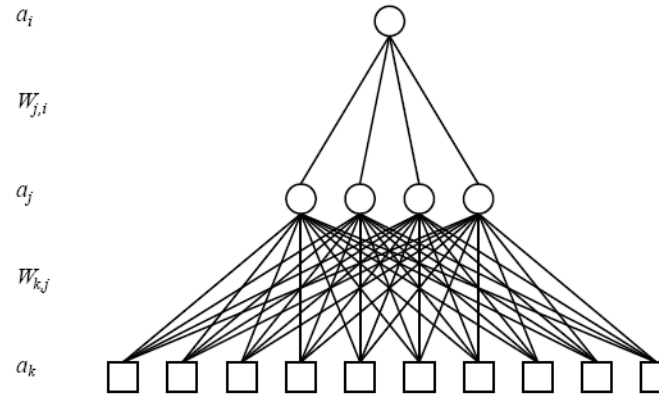
- <https://archive.ics.uci.edu/ml/index.php>
- <https://www.kaggle.com/datasets>
- <https://data.go.id/>

- <https://www.kaggle.com/ronitf/heart-disease-uci>
- [http://faculty.neu.edu.cn/yunhyan/NEU surface defect database.html](http://faculty.neu.edu.cn/yunhyan/NEU_surface_defect_database.html)

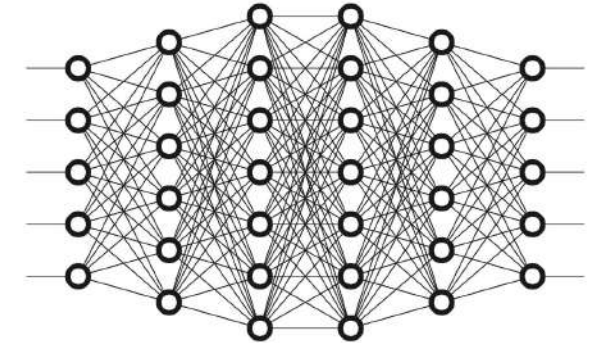
Model ML: Artificial Neural Network (ANN)



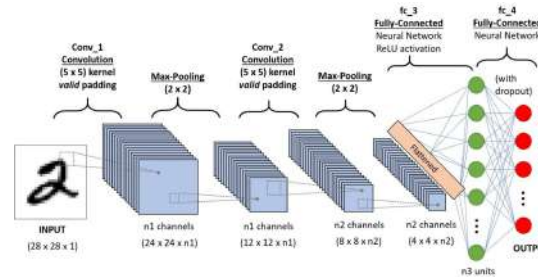
Single Layer Perceptron



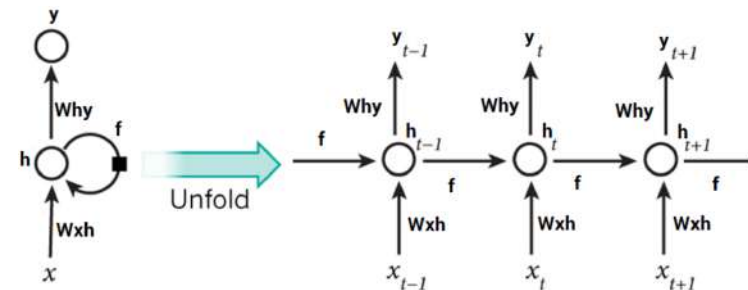
Multi Layer Perceptron



Deep Learning

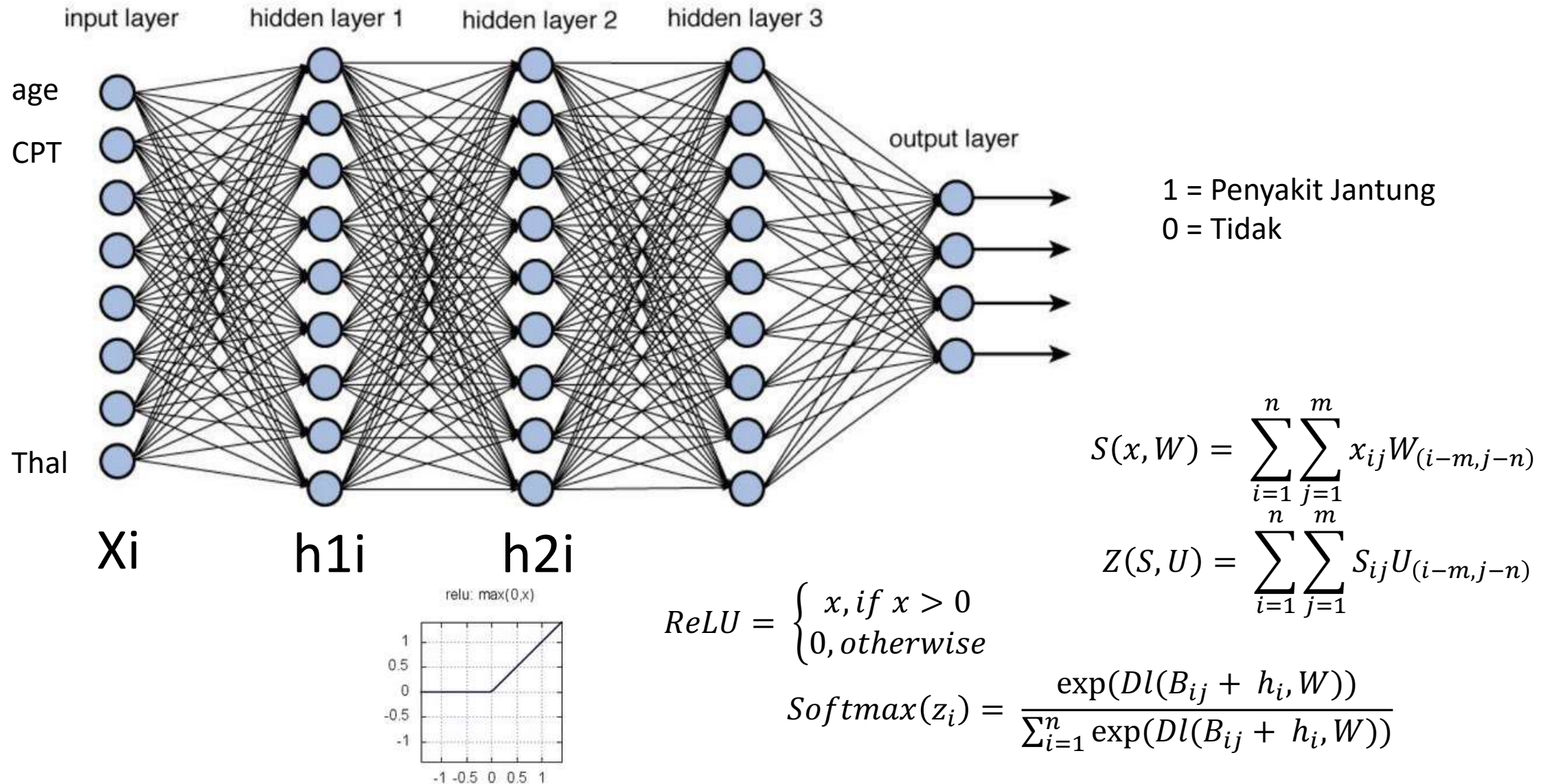


Convolutional Neural Network (CNN)

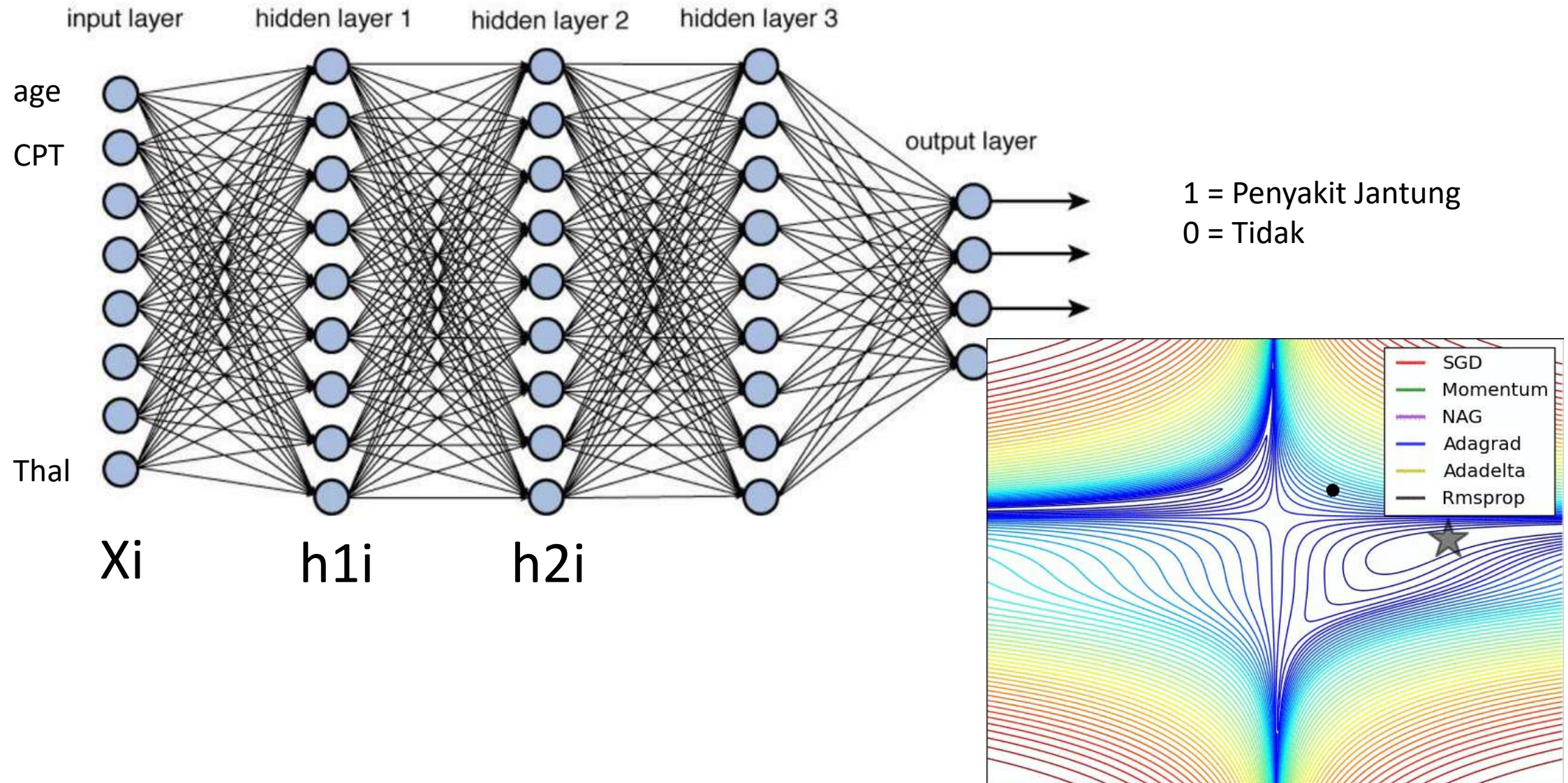


Recurrent Neural Network (RNN)

Algorithm: Deep Neural Networks



Algorithm: Deep Neural Networks

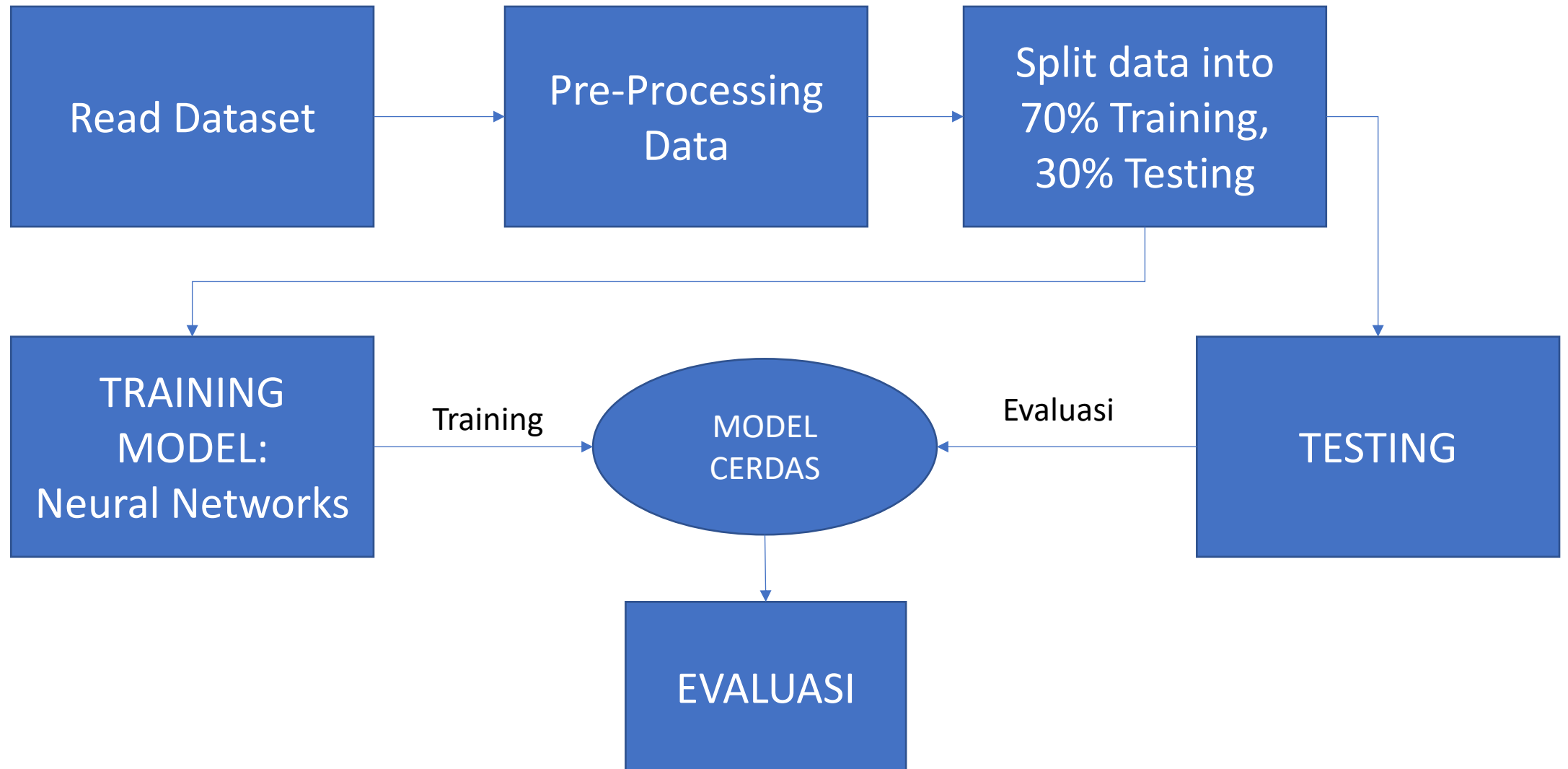


Heart Disease Classification

This database contains 76 attributes, but all published experiments refer **to using a subset of 14 of them**. It is integer valued from 0 (no presence) to 4.

age, sex(1 = male; 0 = female), cpchest pain type, trestbpsresting blood pressure, cholserum cholestoral, fbs(fasting blood sugar > 120 mg/dl) (1 = true; 0 = false), restecgresting electrocardiographic results thalachmaximum heart rate achieved, exangexercise induced angina (1 = yes; 0 = no), oldpeakST depression induced by exercise relative to rest slopethe slope of the peak exercise ST segment canumber of major vessels (0-3) colored by flourosopy, thal3 = normal; 6 = fixed defect; 7 = reversable defect target1 or 0

Flow Classification Heart Disease



Create Model

```
model = Sequential()  
n_cols = X_train.shape[1]  
model.add(Dense(10, activation='relu',  
                input_shape=(n_cols,)))  
model.add(Dense(10, activation='relu'))  
model.add(Dense(2, activation='softmax'))  
model.compile(optimizer='adam',  
              loss='categorical_crossentropy',  
              metrics=['accuracy'])
```


Create Model

```
model.summary()
```

Layer (type)	Output Shape	Param #
dense_16 (Dense)	(None, 10)	140
dense_17 (Dense)	(None, 10)	110
dense_18 (Dense)	(None, 2)	22

Checkpoint Training

- `#Checkpoint in Training`
- `filepath="w{epoch:02d}-{val_acc:.2f}.hdf5"`
- `checkpoint = ModelCheckpoint(filepath,
 monitor='val_acc', verbose=1,
 save_best_only=True, mode='max')`
- `#Logger`
- `csv_logger = CSVLogger('log.csv',
 append=True, separator=';')`

Training

- #Training Model
- `model.fit(X_train, y_train, validation_split=0.2, epochs=100, callbacks=[csv_logger, checkpoint])`

```
Train on 169 samples, validate on 43 samples
Epoch 1/100
169/169 [=====] - 0s 3ms/step - loss: 0.3526 - acc: 0.8284 - val_loss: 0.4824 - val_acc: 0.7674

Epoch 00001: val_acc improved from -inf to 0.76744, saving model to w01-0.77.hdf5
Epoch 2/100
169/169 [=====] - 0s 82us/step - loss: 0.3319 - acc: 0.8698 - val_loss: 0.5189 - val_acc: 0.7674
```

Model Save / Load

#Model Save

- `model.save("model.h5")`

#Model Load

- `model_baru = load_model('model.h5')`

- `model_baru.summary()`

Testing

```
y_pred = model.predict_classes(X_test)
y_test_ = np.argmax(y_test, axis=1)
print(classification_report(y_test_,
y_pred, target_names=["Sakit", "Tidak"]))
```

	precision	recall	f1-score	support
Sakit	0.77	0.80	0.79	41
Tidak	0.83	0.80	0.82	50
avg / total	0.80	0.80	0.80	91

Model Evaluation

- Precision (P) = $\frac{|Relevant \cap Retrieved|}{|Retrieved|}$
- Recall (R) = $\frac{|Relevant \cap Retrieved|}{|Relevant|}$
- F-Score (F) = $2 \frac{P \cdot R}{P + R}$
- Kappa = $\frac{P(A) - P(E)}{P(E) - 1}$

Precision Recall + Confusion Matrix

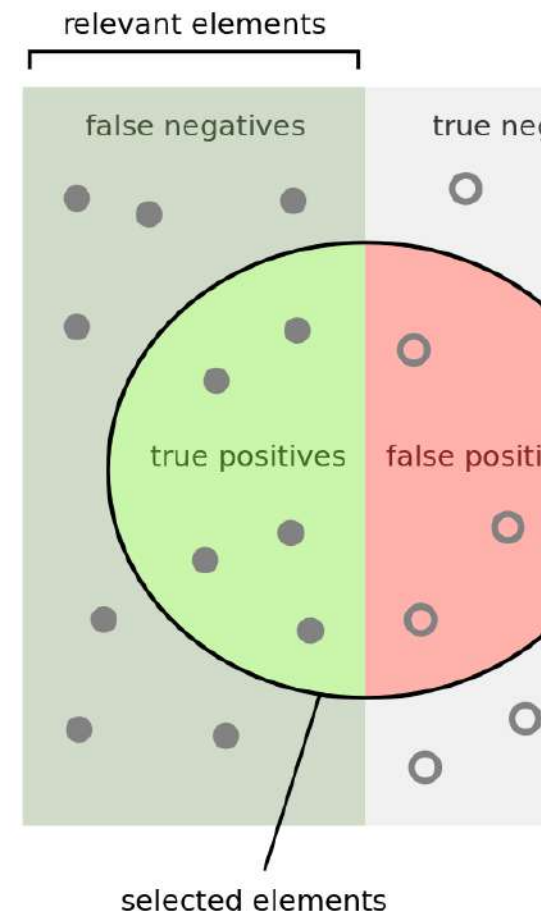
$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

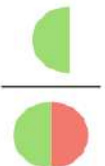
$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

```
[[249, 0, 8, 0, 10, 0, 7, 4, 0],
 [ 0, 261, 4, 0, 0, 0, 0, 1, 4],
 [ 15, 3, 232, 0, 1, 0, 0, 2, 0],
 [ 0, 0, 0, 363, 0, 7, 1, 0, 0],
 [ 63, 1, 7, 16, 14, 5, 13, 12, 0],
 [ 1, 0, 0, 35, 1, 15, 11, 0, 0],
 [ 0, 0, 0, 0, 0, 0, 393, 1, 0],
 [ 2, 0, 0, 0, 0, 0, 2, 514, 0],
 [ 0, 55, 2, 0, 0, 0, 0, 0, 50]]
```



How many selected items are relevant?

Precision =



How many items are selected?

Recall =

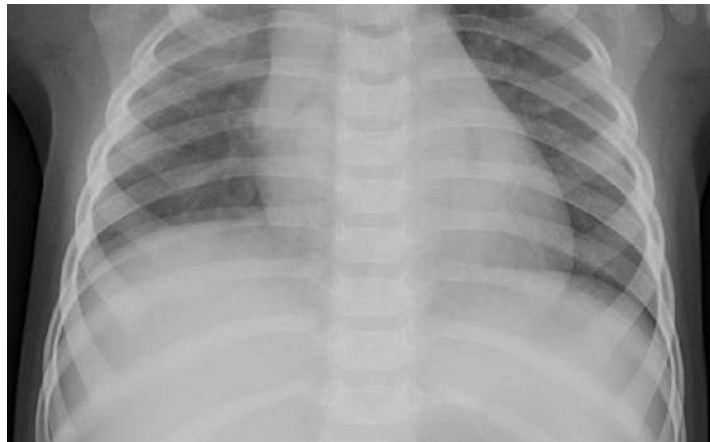
Medical Image Classification

Pneumonia Image Classification

This database contains of X-Ray images normal Chest, Pneumonia caused by virus and Pneumonia caused by bacteria.



Normal

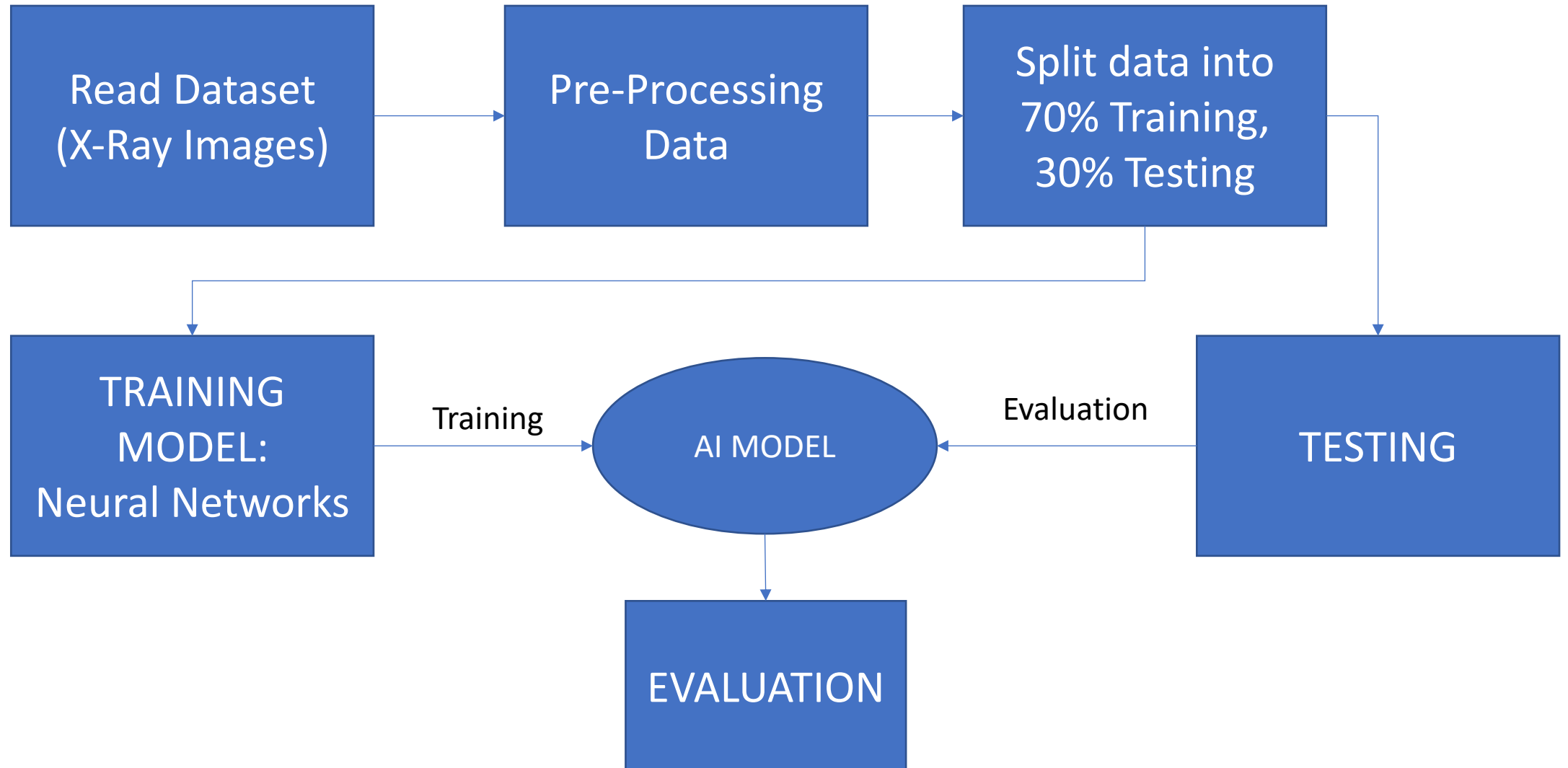


Bacteria



Virus

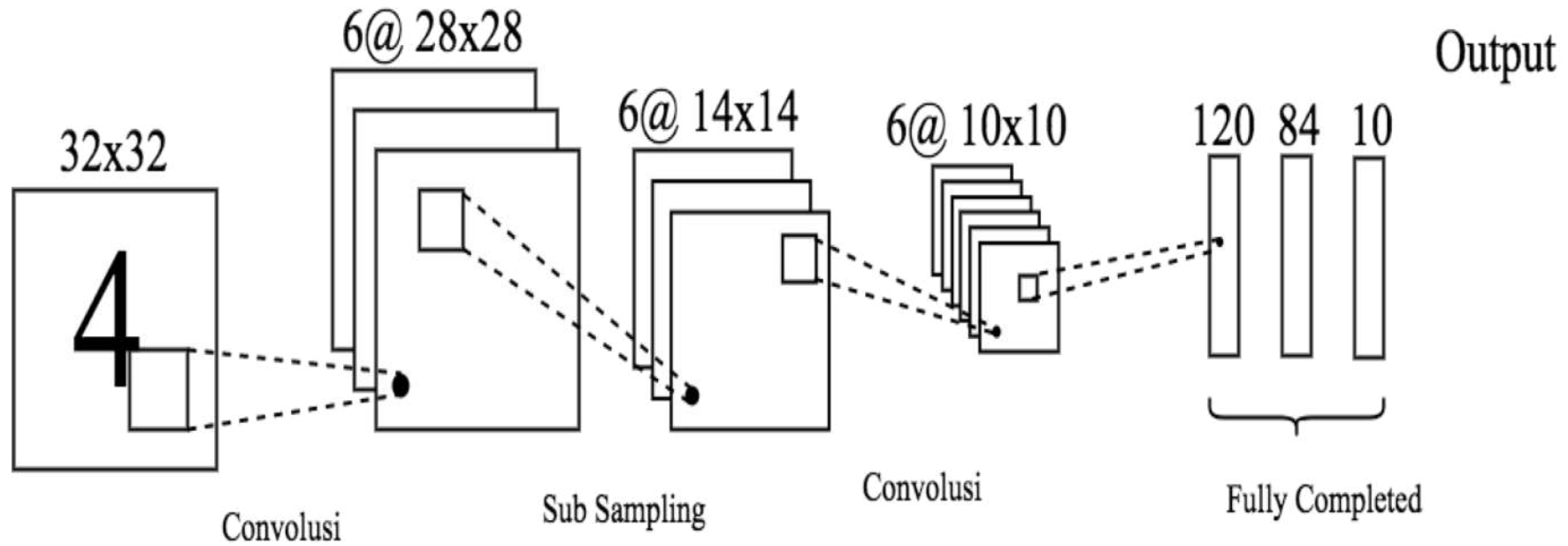
Flow Classification Pneumonia Disease



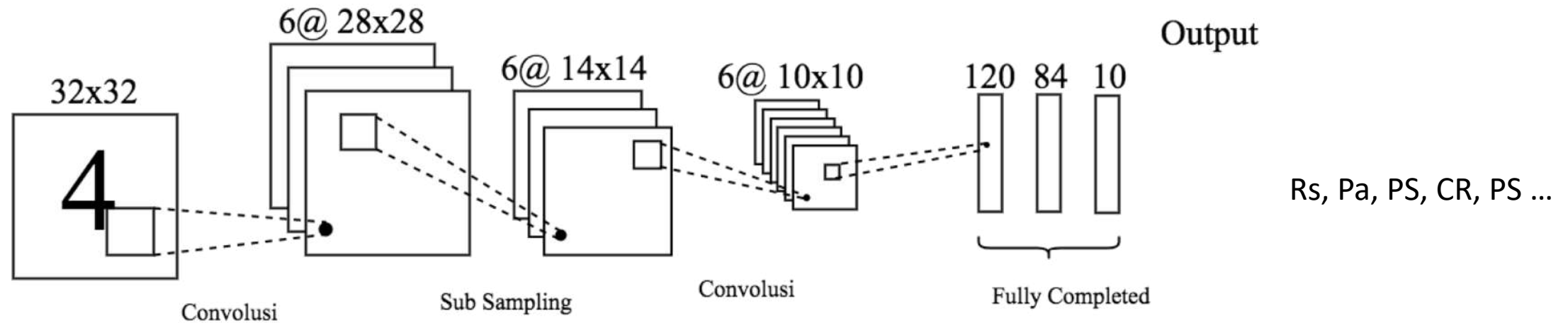
**In order to classify images, we Need variant of Neural Networks for
Image Classification!**

CONVOLUTIONAL NEURAL NETWORKS

Deep Convolutional Neural Networks



Convolutional Neural Networks



$$S(x, W) = \sum_{i=1}^n \sum_{j=1}^m x_{ij} W_{(i-m, j-n)}; \quad Z(S, U) = \sum_{i=1}^n \sum_{j=1}^m S_{ij} U_{(i-m, j-n)}; \quad \text{Softmax}(z_i) = \frac{\exp(Z_i)}{\sum_{i=1}^n \exp(Z_j)}$$

Convolution Example

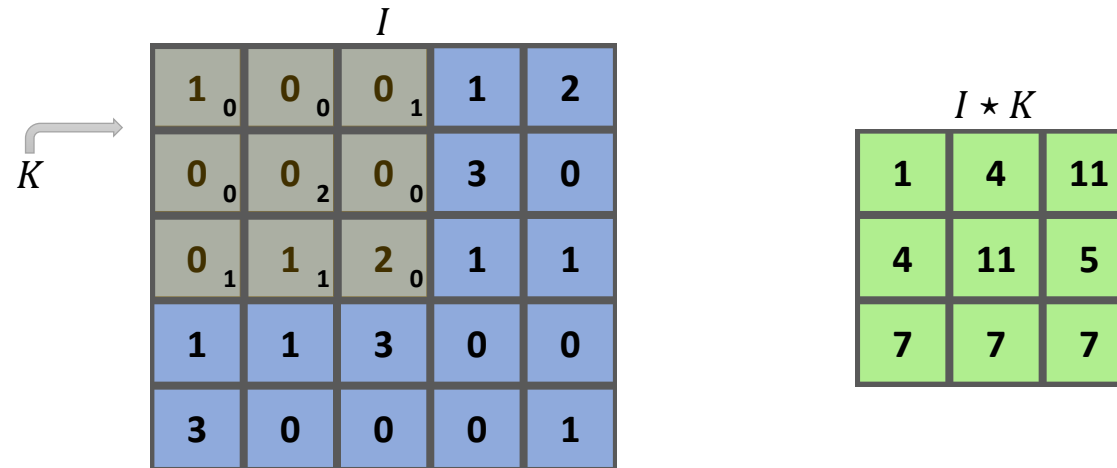
I						K		
1	0	0	1	2	★	0	0	1
0	0	0	3	0		0	2	0
0	1	2	1	1		1	1	0
1	1	3	0	0				
3	0	0	0	1				

$$\begin{aligned}(I \star K)(0,0) &= I(0,0)K(0,0) + I(0,1)K(0,1) + I(0,2)K(0,2) + \\ &\quad I(1,0)K(1,0) + I(1,1)K(1,1) + I(1,2)K(1,2) + \\ &\quad I(2,0)K(2,0) + I(2,1)K(2,1) + I(2,2)K(2,2) \\ &= 1 \cdot 0 + 0 \cdot 0 + 0 \cdot 1 + \\ &\quad 0 \cdot 0 + 0 \cdot 2 + 0 \cdot 0 + \\ &\quad 0 \cdot 1 + 1 \cdot 1 + 2 \cdot 0 \\ &= 1\end{aligned}$$

$$(I \star K)(i,j) = \sum_m \sum_n I(m,n)K(i+m,j+n)$$

Convolution Example

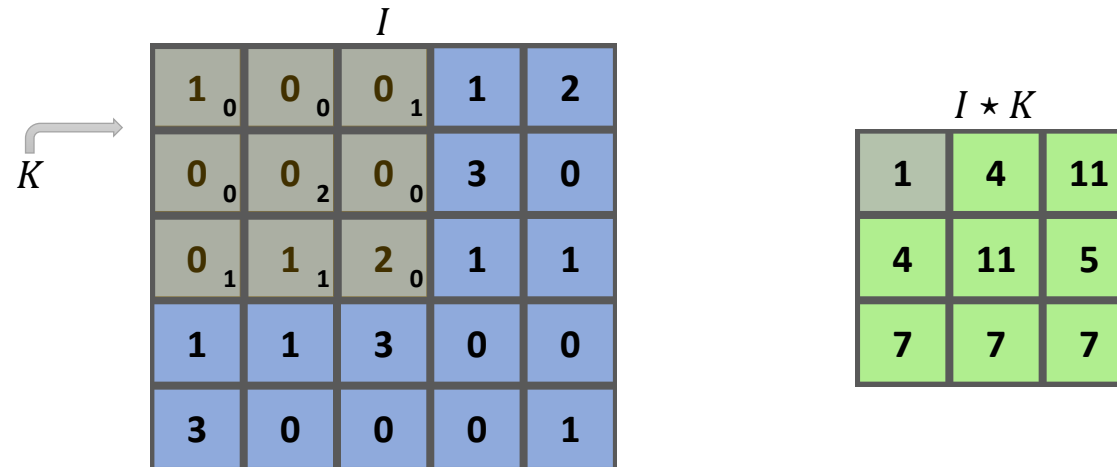
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

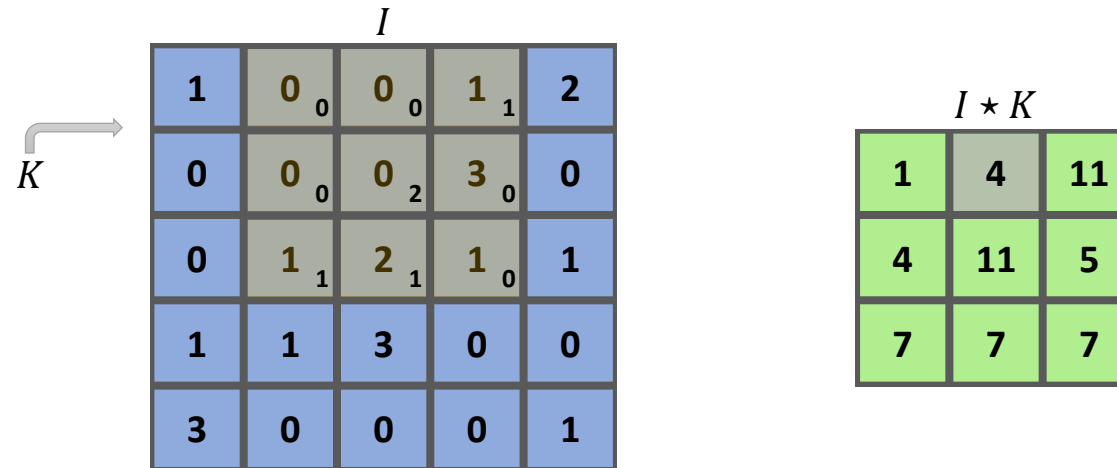
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$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

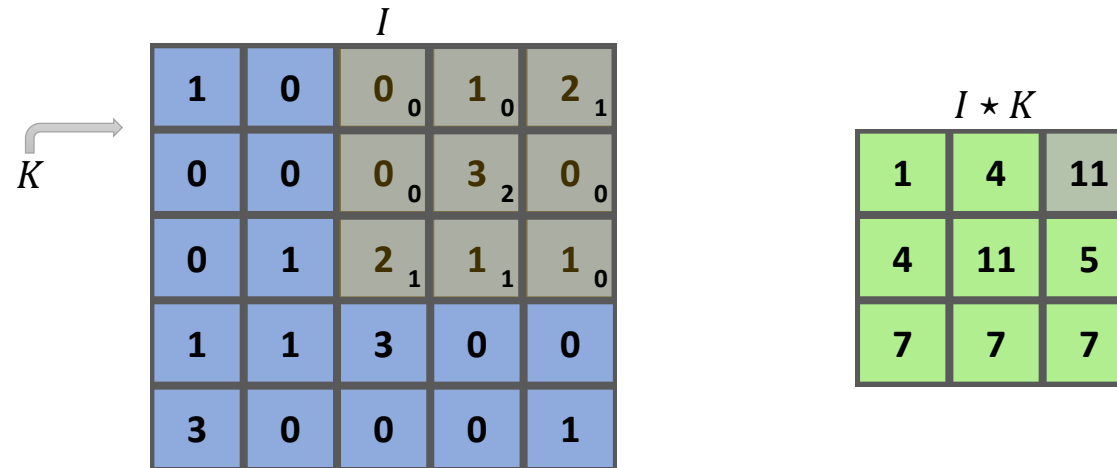
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

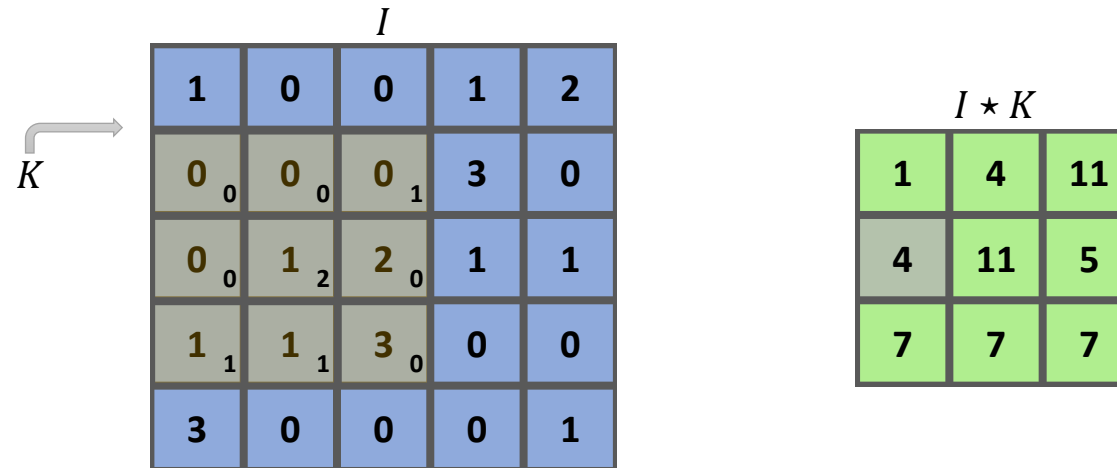
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

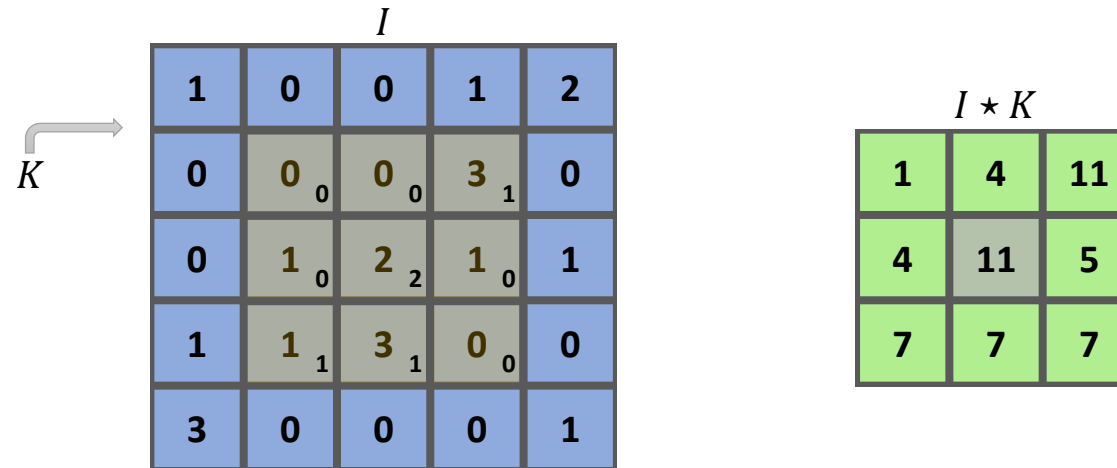
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

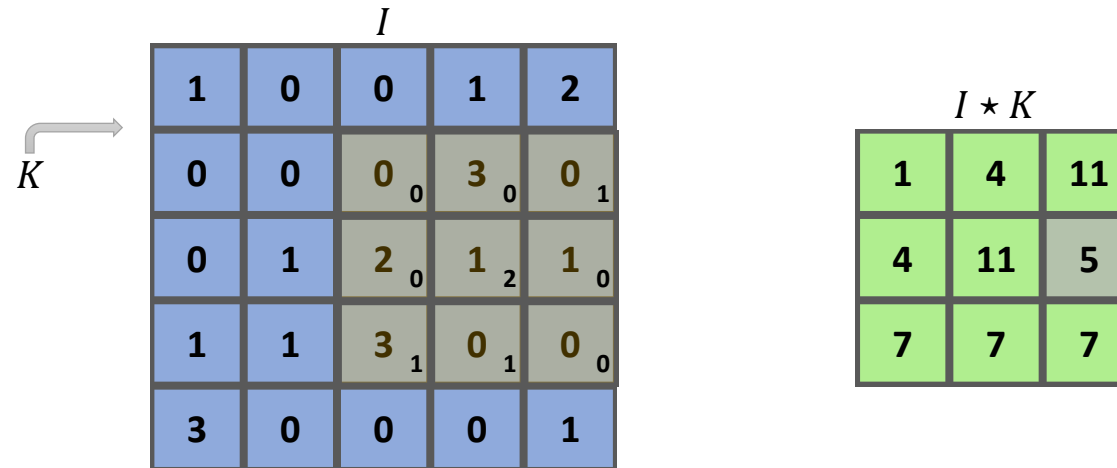
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

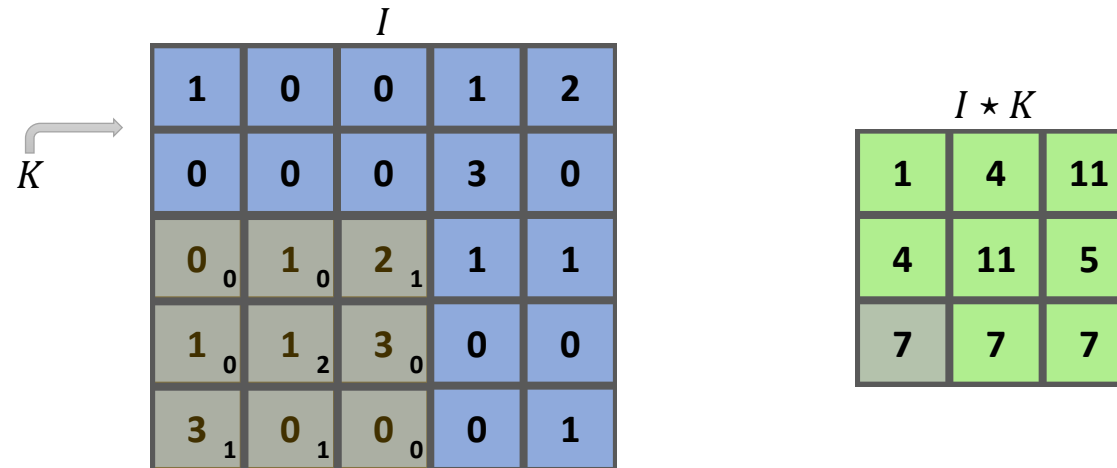
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) = \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

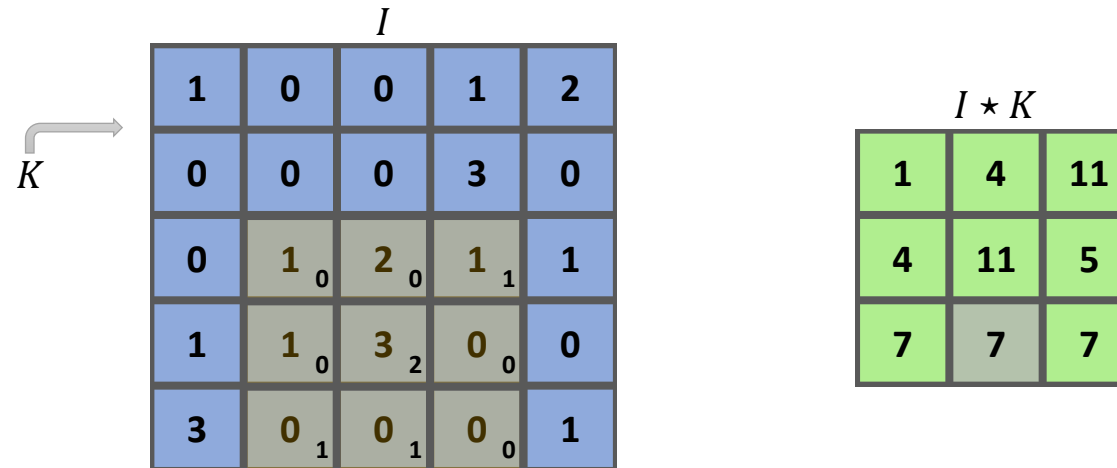
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

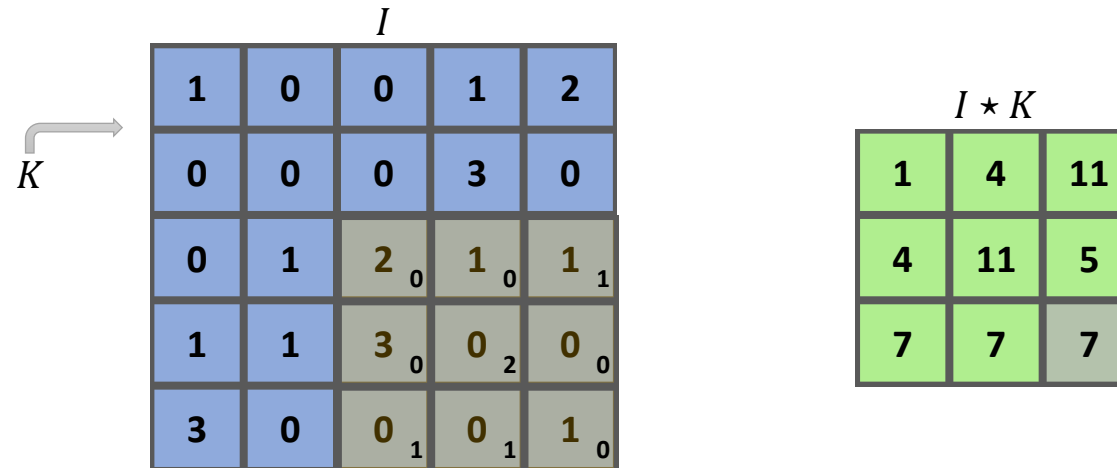
Can be viewed as a “sliding window” operation:



$$(I \star K)(i, j) == \sum_m \sum_n I(m, n) K(i + m, j + n)$$

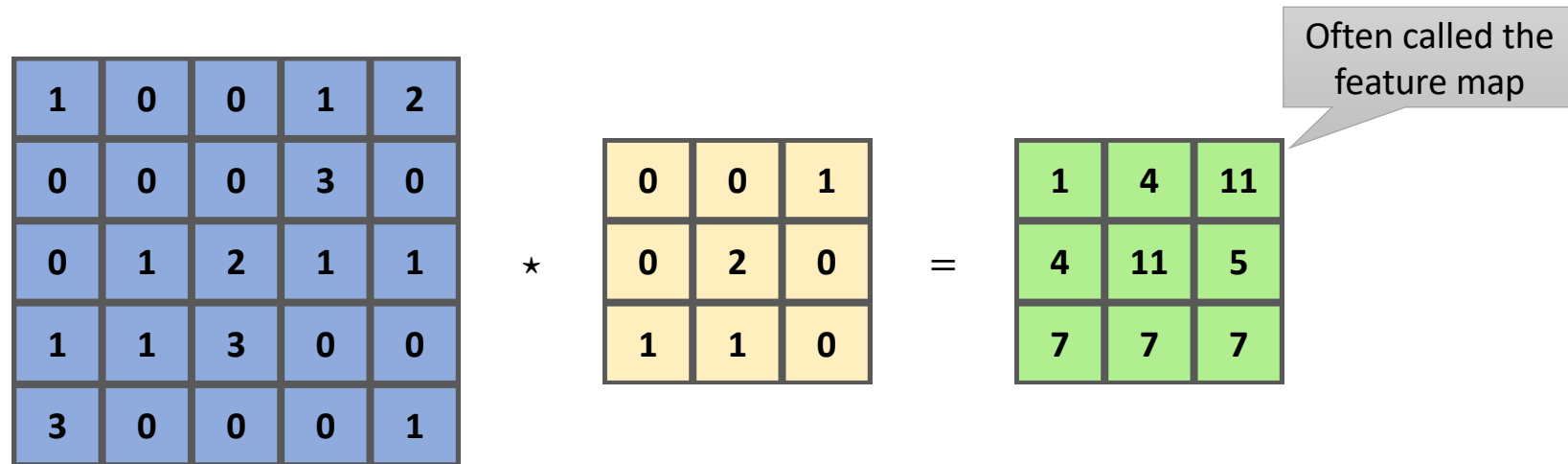
Convolution Example

Can be viewed as a “sliding window” operation:



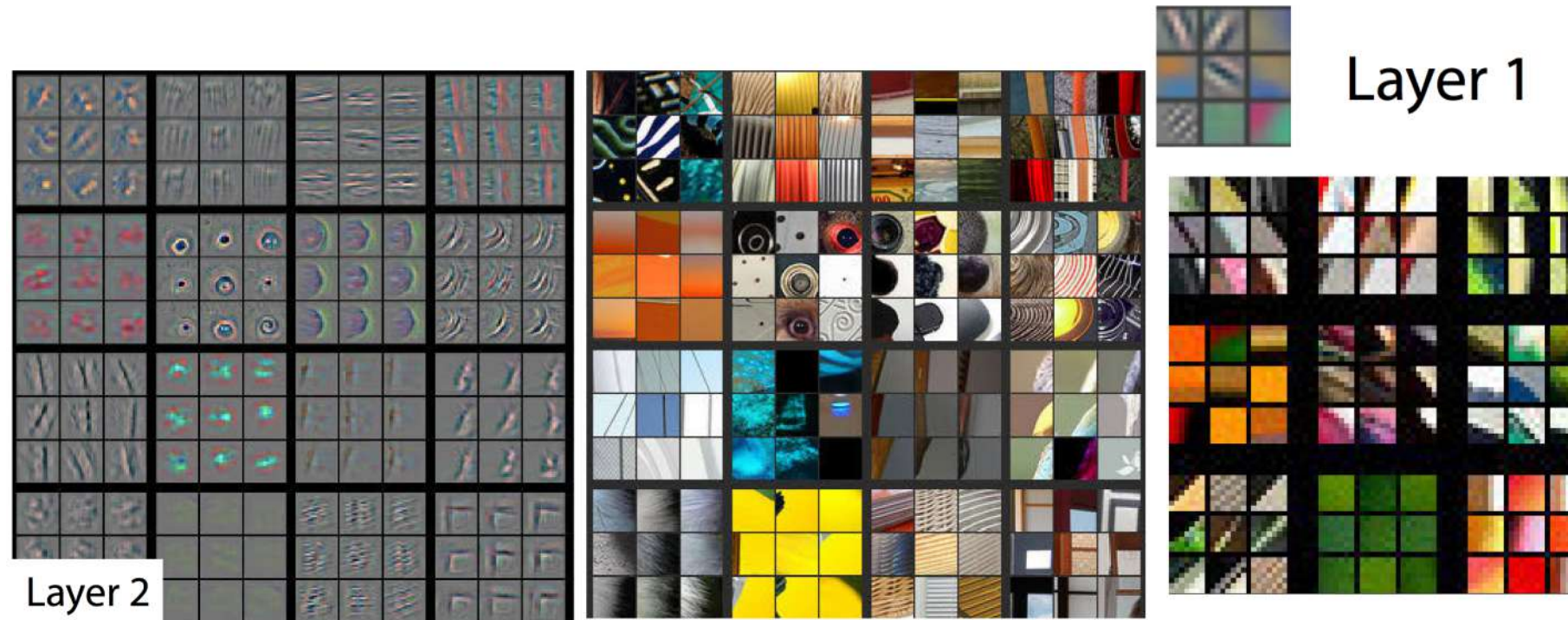
$$(I \star K)(i, j) = \sum_m \sum_n I(m, n) K(i + m, j + n)$$

Convolution Example

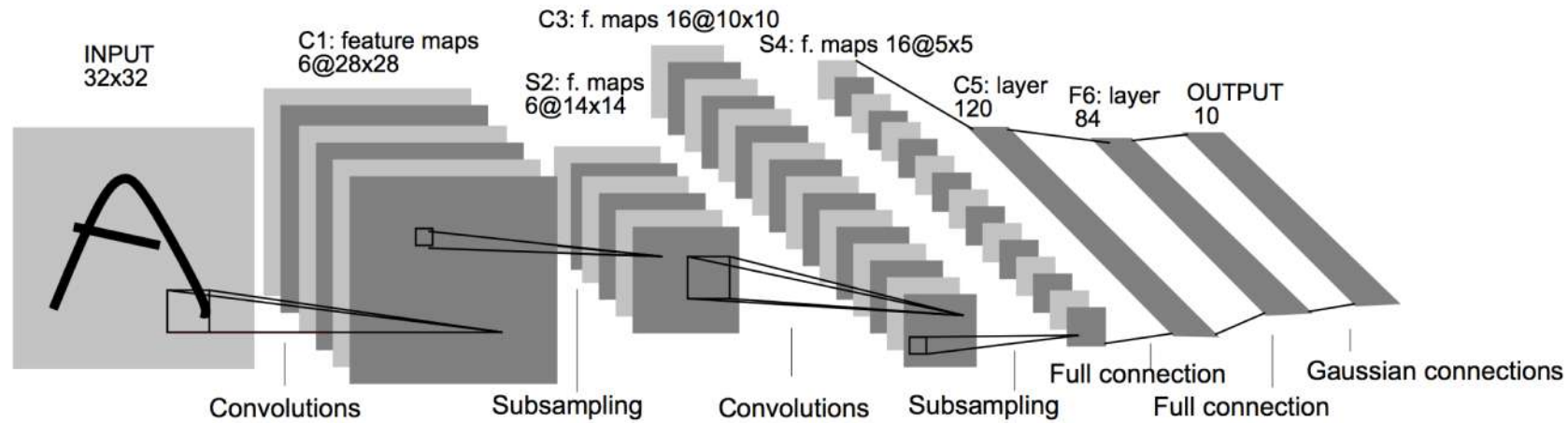


$$(I \star K)(i, j) = \sum_m \sum_n I(m, n) K(i + m, j + n)$$

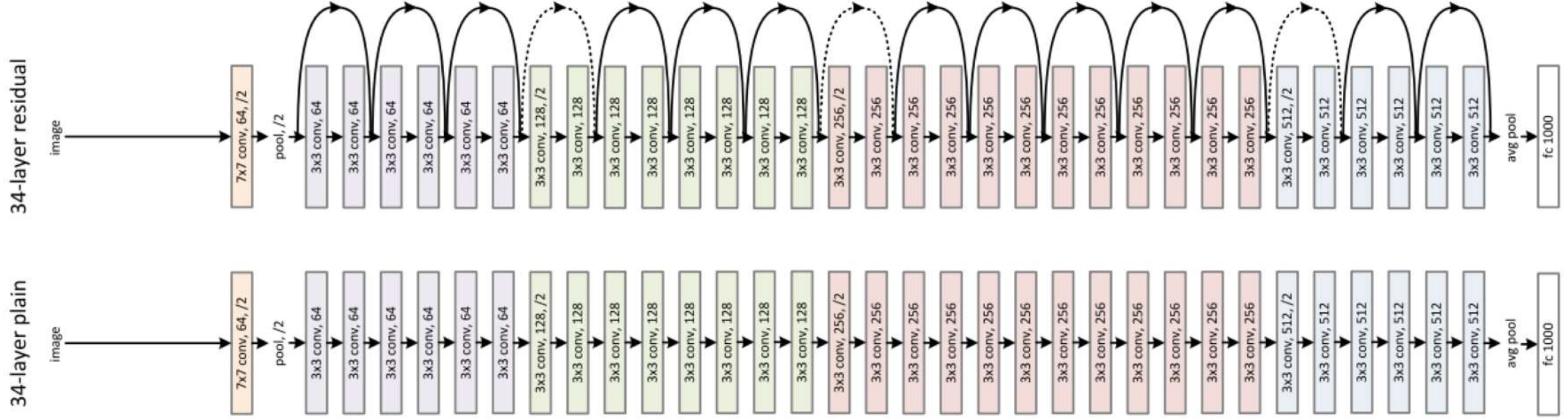
Feature Visualization



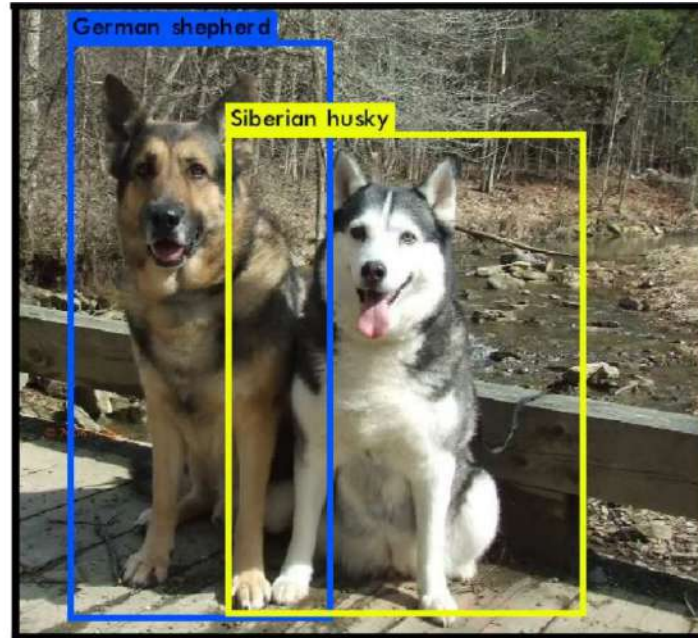
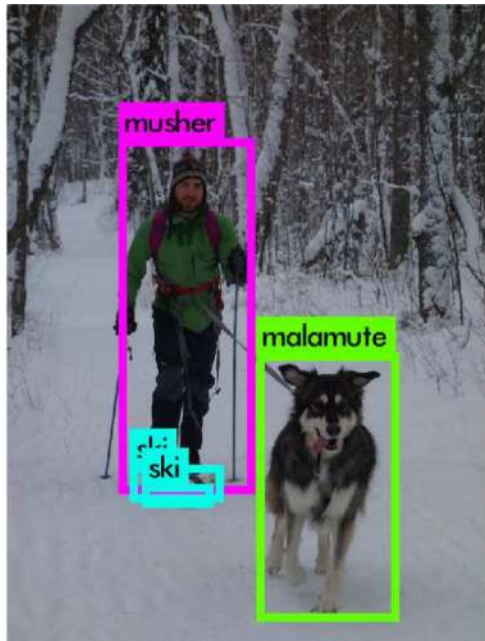
Variant CNN: AlexNet



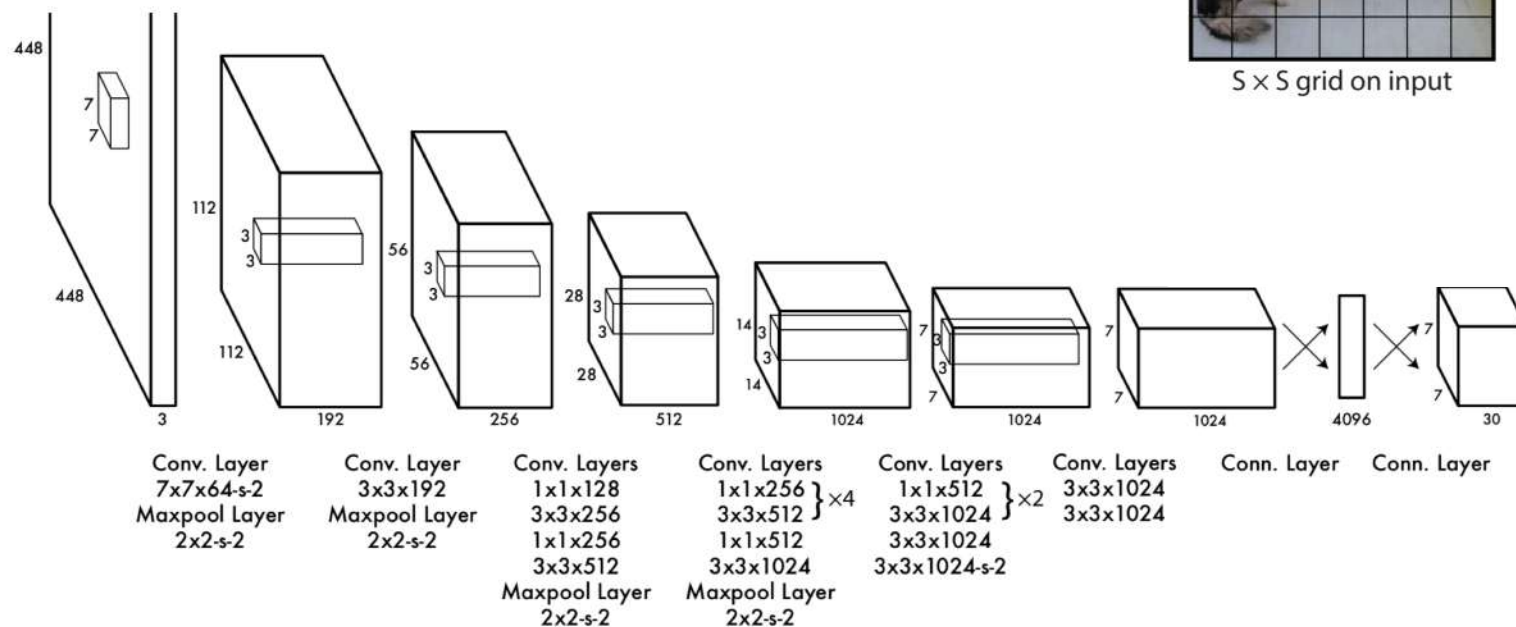
Variant CNN: ResNet



Variant CNN: Object Detection



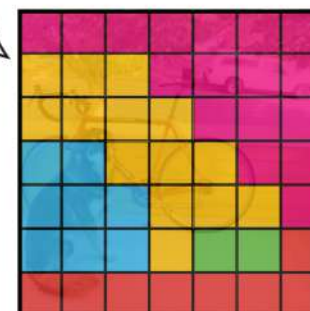
Variant CNN: YOLO



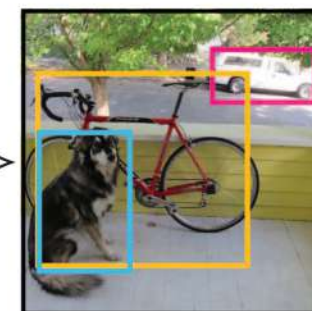
5×5 grid on input



Bounding boxes + confidence



Class probability map



Final detections

Read Dataset

```
path = os.path.abspath('chestxray.ipynb')
path = re.sub('[a-zA-Z\s._]+$', '', path)
dirs = os.listdir(path+'../dataset/xray/')
label = 0
X = []
y = []
example_data = []
example_label = []
```

Read Dataset

```
for i in dirs: #loop all directory
    count = 0 #Temporary variable count
    for pic in glob.glob(path+'/*.jpeg'):
        im = cv2.imread(pic)
        im = cv2.resize(im, (100,100))
        im = np.array(im)
        count = count + 1
        X.append(im)
        y.append(label)
```

Read Dataset

```
if (count==3) :  
    example_data.append({str(i) : im})  
    example_label.append(i)  
    label = label + 1  
    X = np.array(X)  
    y = np.array(y)
```

Data Split

```
X_train, X_test, y_train, y_test =  
train_test_split(X, y, test_size=0.33,  
random_state=42)
```

```
X_train = X_train.astype('float32')
```

```
X_test = X_test.astype('float32')
```

```
X_train /= 255
```

```
X_test /= 255
```

```
y_train = to_categorical(y_train, 3)
```

```
y_test = to_categorical(y_test, 3)
```


Model Creation

```
model = Sequential()  
model.add(Conv2D(32, kernel_size=(3,  
3), activation='relu', input_shape=(100,100,3)))  
model.add(MaxPooling2D(pool_size=(2,2)))  
model.add(Conv2D(32, (3, 3), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2,2)))  
model.add(Dropout(0.25))  
model.add(Flatten())  
model.add(Dense(128, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(9, activation='softmax'))
```

Model Compile

```
epochs = 25
lr = 0.01
decay = lr/epochs
sgd = SGD(lr=lr, momentum=0.9, decay=decay,
nesterov=False)
model.compile(loss='categorical_crossentropy',
optimizer=sgd, metrics=['accuracy'])
print(model.summary())
```

Model Training

```
model.fit(X_train, y_train,  
validation_data=(X_test, y_test), epochs=epochs,  
batch_size=32)  
  
scores = model.evaluate(X_test, y_test, verbose=0)  
print("Accuracy: %.2f%%" % (scores[1]*100))
```

Model Evaluation

```
model = model.save('my_model.h5')  
model_baru = load_model('my_model.h5')  
y_pred = model_baru.predict_classes(X_test)  
y_test_ = np.argmax(y_test, axis=1)  
print(classification_report(y_test_, y_pred,  
target_names=mapping.values()))
```

Precision Recall + Confusion Matrix

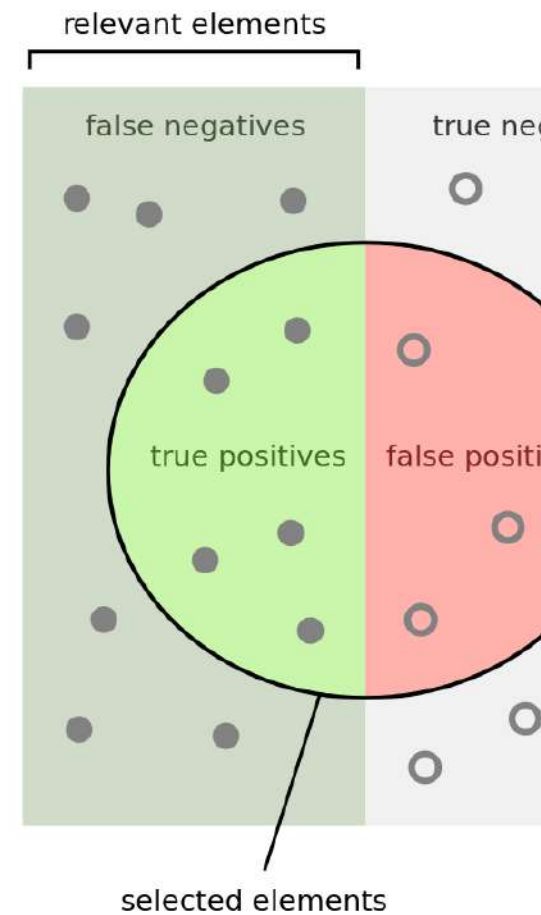
$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

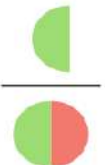
$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

```
[[249, 0, 8, 0, 10, 0, 7, 4, 0],
 [ 0, 261, 4, 0, 0, 0, 0, 1, 4],
 [ 15, 3, 232, 0, 1, 0, 0, 2, 0],
 [ 0, 0, 0, 363, 0, 7, 1, 0, 0],
 [ 63, 1, 7, 16, 14, 5, 13, 12, 0],
 [ 1, 0, 0, 35, 1, 15, 11, 0, 0],
 [ 0, 0, 0, 0, 0, 0, 393, 1, 0],
 [ 2, 0, 0, 0, 0, 0, 2, 514, 0],
 [ 0, 55, 2, 0, 0, 0, 0, 0, 50]]
```



How many selected items are relevant?

Precision =



How many items are selected?

Recall =

Result

	precision	recall	f1-score	support
NORMAL	0.86	0.87	0.86	83
PNEUMONIA	0.91	0.90	0.91	123
accuracy			0.89	206
macro avg	0.88	0.88	0.88	206
weighted avg	0.89	0.89	0.89	206

Exercise: Skin Cancer Classification

Read skin cancer dataset using the similar techniques as chest x-ray. Classify the image whether the sample images benign or malignant.

Use appropriate techniques like image preprocessing or feature selection to improve your model

The final result is **we can create the model that can classify the image whether malignant or benign**