

in Invision

Concepts, Architecture and Applications

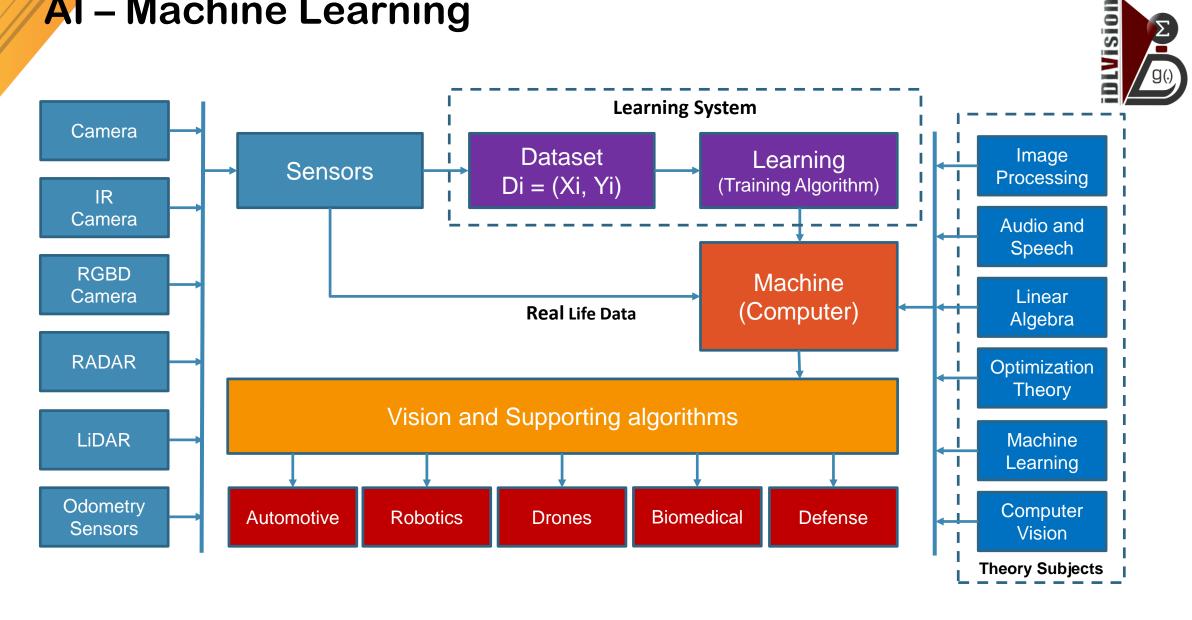


## Objective: AI - ML - DL - CNN

• Understand concepts: AI - CV - ML - DL - CNN

- Approach / Perception to learn Methodology
- Technology HW, SW requirements
- Applications / Use cases
- Future and Scope

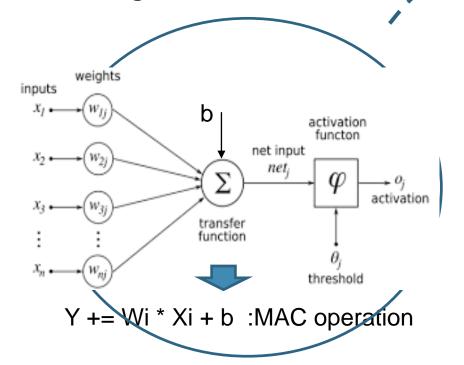
## Al – Machine Learning



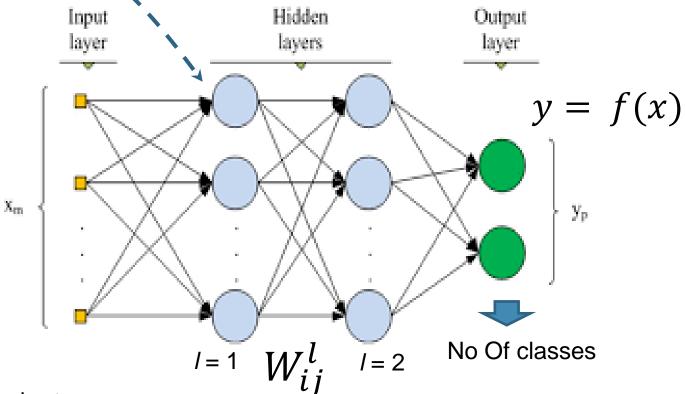
## CNN - Neural Net classifier



### Single Neuron architecture



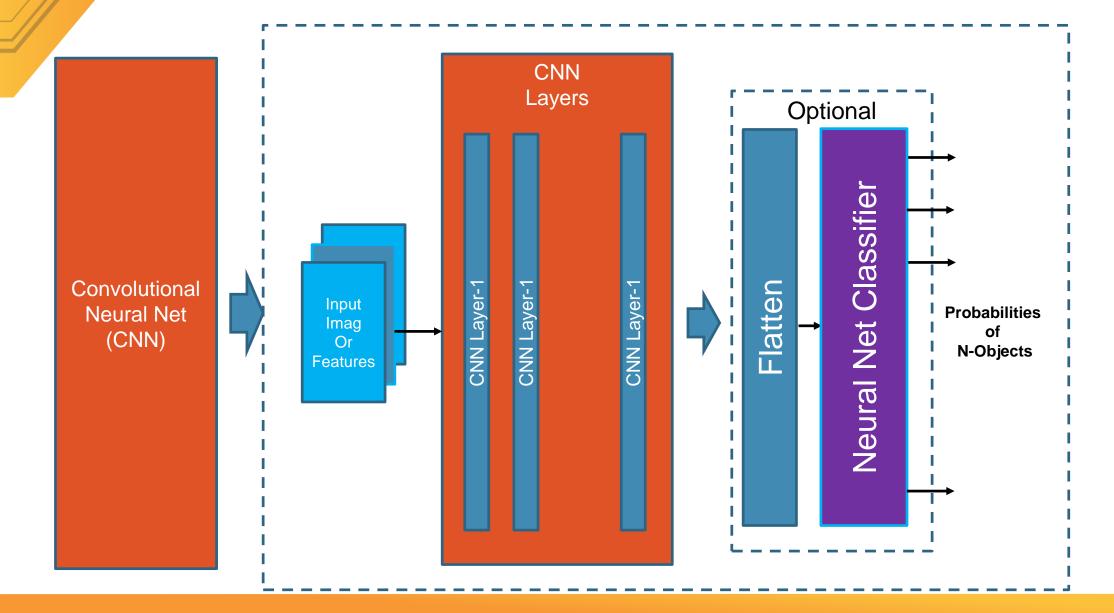
#### **MLP: Fully Connected Neural Net**



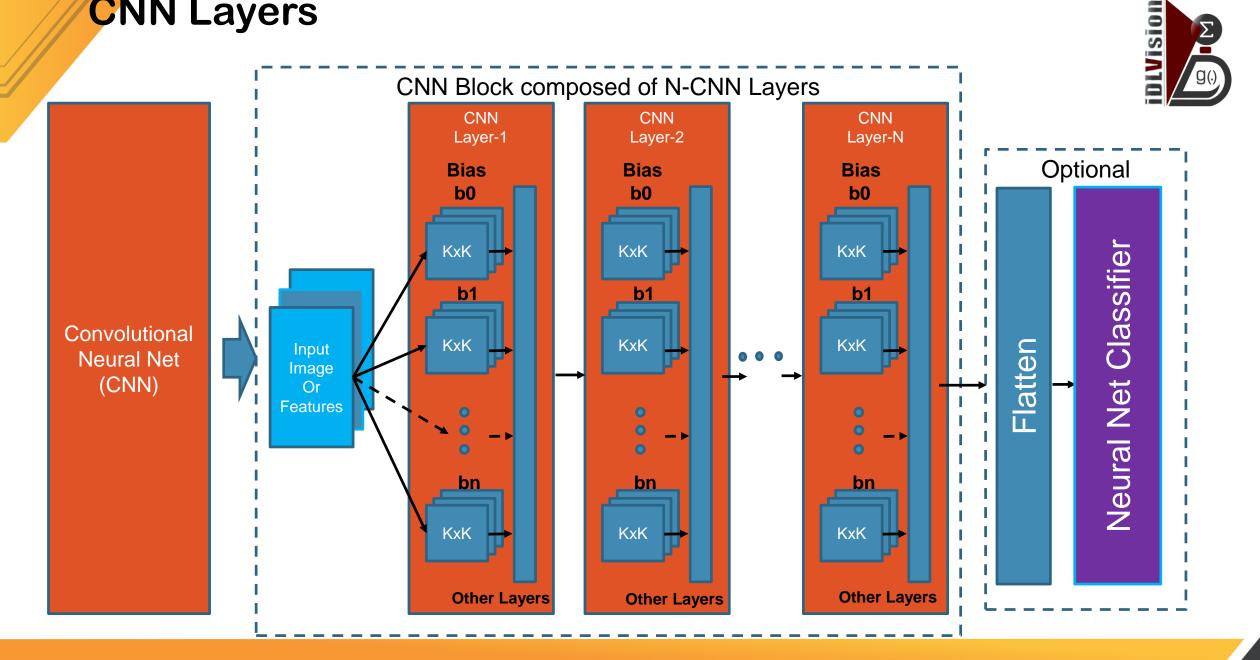
Activation function = Nonlinear function => exp, tanh etc

## Convolutional Neural Net (CNN) Model



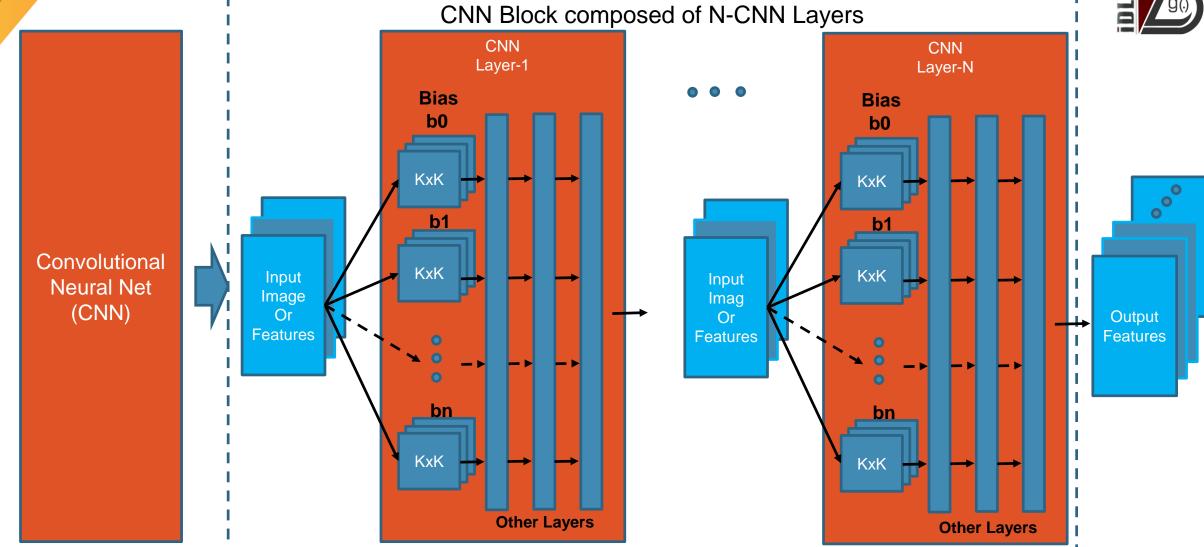


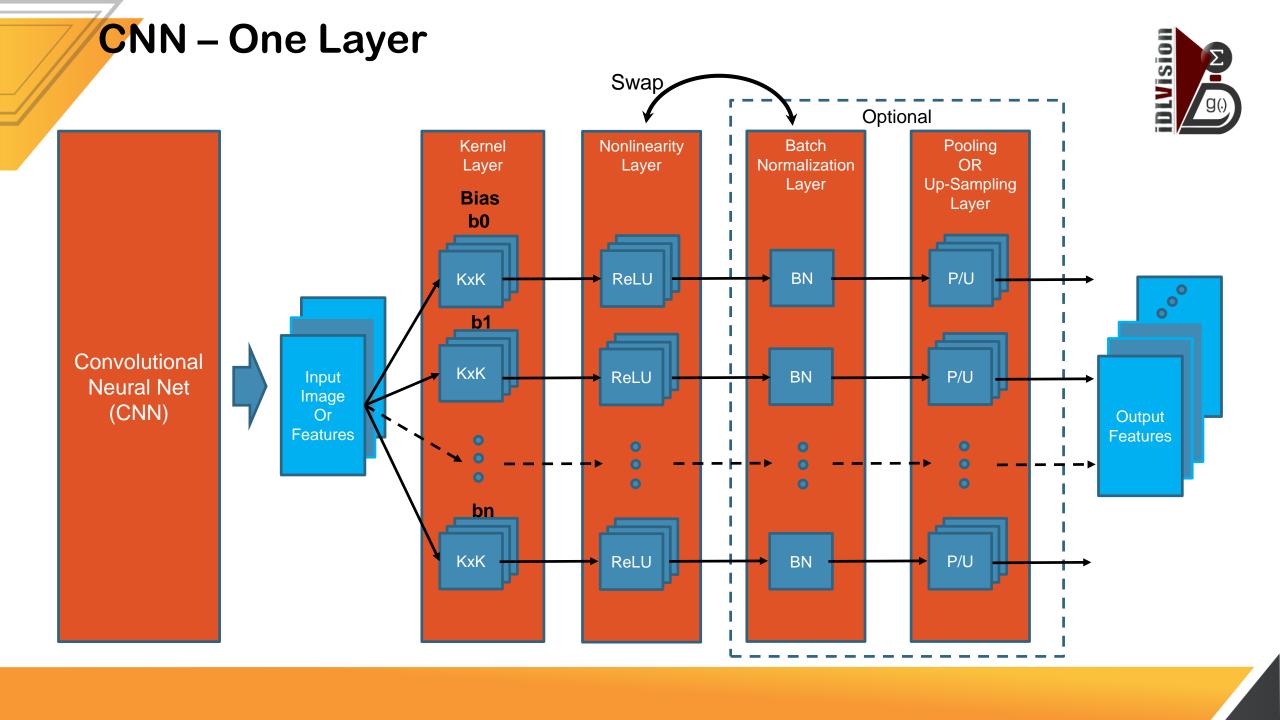
## **CNN** Layers



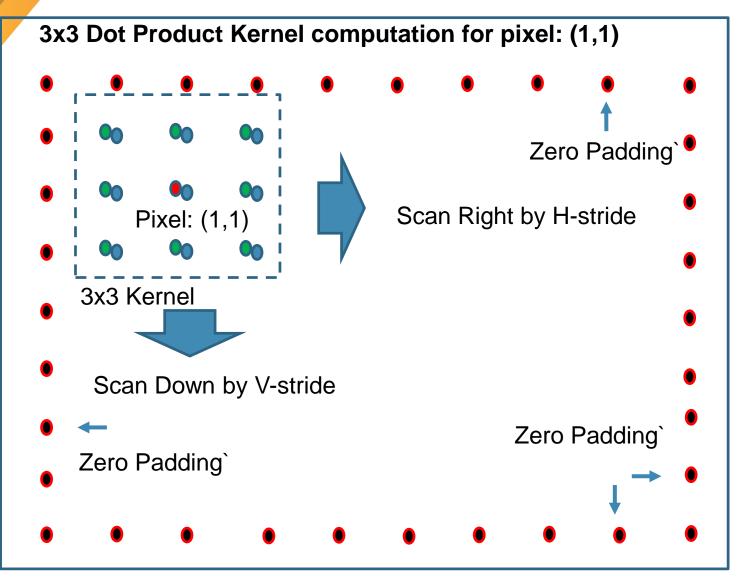
# **CNN** Layers





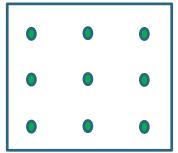


## **CNN** – Kernel Filtering operation





#### 3x3 Kernel

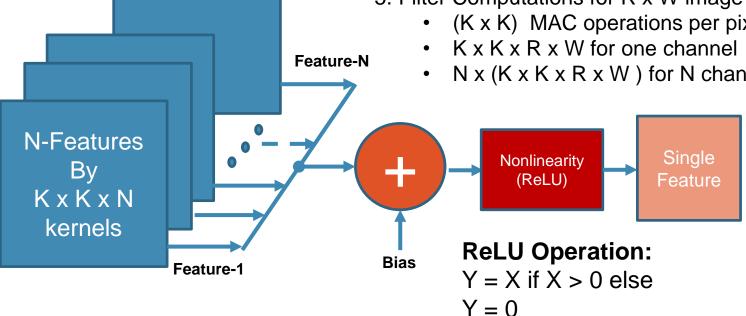


- 1. Padding is optional but used 99%
- 2. It keeps size of filtered output feature image same
- 3. Channels of kernel = number of input features
- 4. Number of kernels is defined by user. Typically, gets doubled to next layer
- 5. In kernel convolution operation
  - Dot product is calculated for pixel with kernel center is position on pixel
  - Kernel is moved in Raster scan fashion in horizontal and then next row by stride amount
  - Stride is typically(1,1)
  - Higher value of stride is used to reduce the size of feature output in orde to reduce computations in DL model

## **CNN** – Single Kernel Filtering Operation



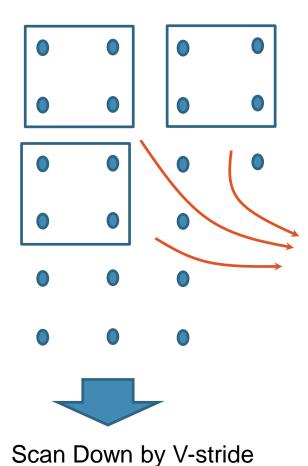
- 1.N channels of (K x K) size kernel produces N filtered images / features
- 2.All filtered images are added at pixel level with bias to generate single image / feature
- 3. Output of adder is passed through Nonlinear operation for each pixel and generates final feature
- 4. The final feature can optionally passed through Batch Normalization and Pooling or Up-sampling
- 5. Filter Computations for R x W image / feature
  - (K x K) MAC operations per pixels
  - $N \times (K \times K \times R \times W)$  for N channels



## **CNN** – Pooling Operation







- 1. Select max out of 4 pixel in Max Pooling
- 2. Select average of all 4 pixel in Average Pooling

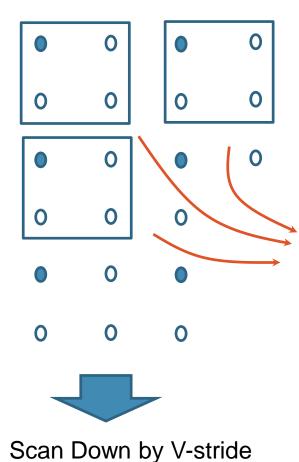
Scan Right by H-stride

- 3. Size is typically (2 x 2) but it can be any integer
- 4. In (2 x 2) stride is 2
- 5. Pooling reduces computations in CNN model and handles dimensionality problem

## **CNN** – Nearest Up-sampling Operation







- Scan Right by H-stride
- 1. Replicate 3 zero pixel by original pixel
- 2. Size is typically (2 x 2) but it can be any integer
- 3. Up-sampling:
  - Improves resolution for better features
  - Required in adder and concatenate blocks to add from previous outputs of higher resolutions
- 4. Bilinear up-sampling can be used for better quality at the cost of increase computations

## CNN – Design Frameworks

- 1. Caffe Opensource from Yann Lecun
- 2. Caffe-2 Opensource improved version of Caffe
- 3. Theano
- 4. CNTK Microsoft
- 5. Torch Facebook
- 6. Tensorflow Google Difficult to understand
- 7. Keras Opensource: Simple to use and very popular

# Include keras libraries to build a DL CNN model

from \_\_future\_\_ import print\_function

import keras from keras.datasets import mnist from keras.models import Sequential

from keras.layers import Dense, Dropout, Flatten from keras.layers import Conv2D, MaxPooling2D from keras import backend as K





#### # Define parameters for DL CNN model

```
batch_size = 128
num_classes = 10
epochs = 12
```

#### # Input image dimensions

img\_rows, img\_cols = 28, 28

#### # Data, segregate for train and test sets

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

```
if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
```

x\_train = x\_train.reshape(x\_train.shape[0], img\_rows, img\_cols, 1)
x\_test = x\_test.reshape(x\_test.shape[0], img\_rows, img\_cols, 1)
input\_shape = (img\_rows, img\_cols, 1)

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#### # Normalize data

x\_train = x\_train.astype('float32')
x\_test = x\_test.astype('float32')
x\_train /= 255
x test /= 255

#### # Print info

print('x\_train shape:', x\_train.shape)
print(x\_train.shape[0], 'train samples')
print(x\_test.shape[0], 'test samples')

#### # Convert class vectors to binary class matrices

y\_train = keras.utils.to\_categorical(y\_train, num\_classes)
y\_test = keras.utils.to\_categorical(y\_test, num\_classes)

#### # Design CNN Model



```
model = Sequential()
```

#### # Add CNN layers

```
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
```

#### # Flatten data before feed it to NN layer

model.add(Flatten())

#### # Define NN layer

```
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
```

#### # Generate the CNN model

```
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adadelta(), metrics=['accuracy'])
```

#### # Train the DL CNN model

```
model.fit(x_train, y_train,
batch_size=batch_size,
epochs=epochs,
verbose=1,
validation_data=(x_test, y_test))
```

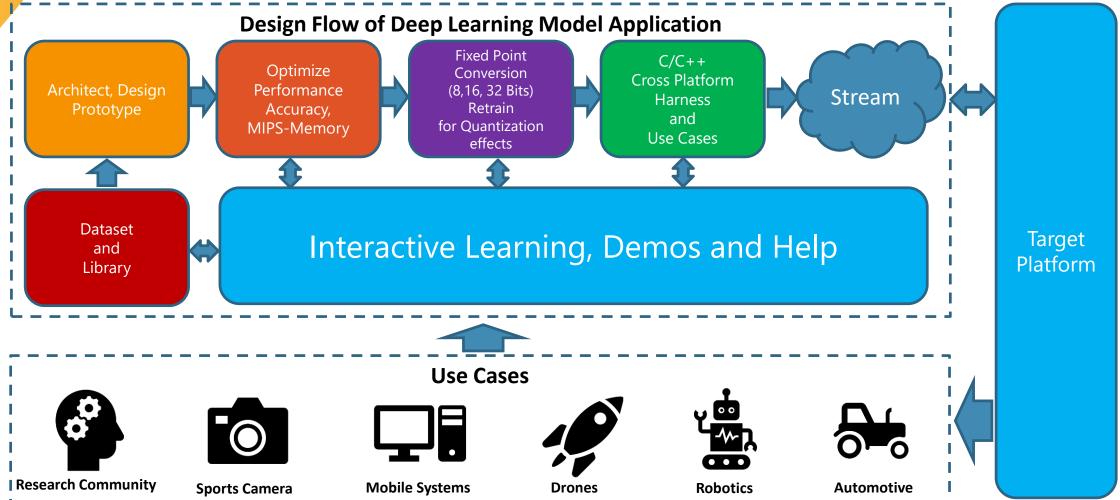
#### # Evaluate the DL CNN model

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```



## **DL** Model CNN - Design Flow







# Thank You!!!



# iDLVision Tech

www.idlvision.com

**Dr. Ganesh Bhokare** 

Q & A