



DEEP NEURAL NETWORKS (DNN)

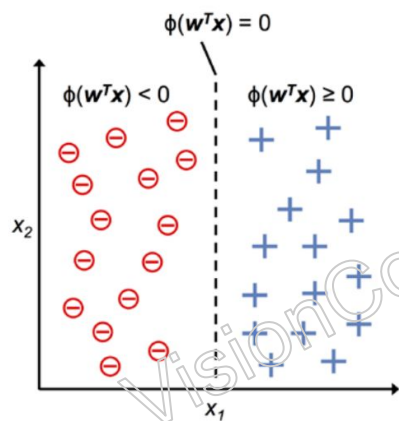
Dr. Ram Prasad K
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ram.krish@visioncog.com
<https://www.visioncog.com>

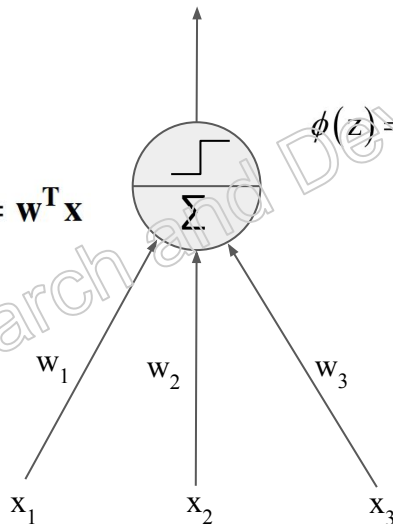
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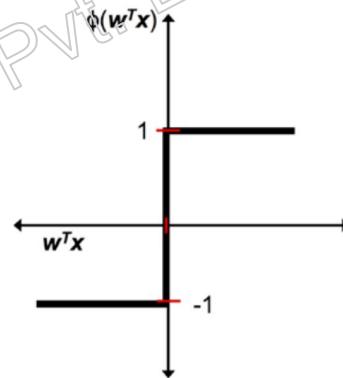
Linear Threshold Unit (LTU)



$$\sum_{j=1}^n w_j x_i = \mathbf{w}^T \mathbf{x}$$



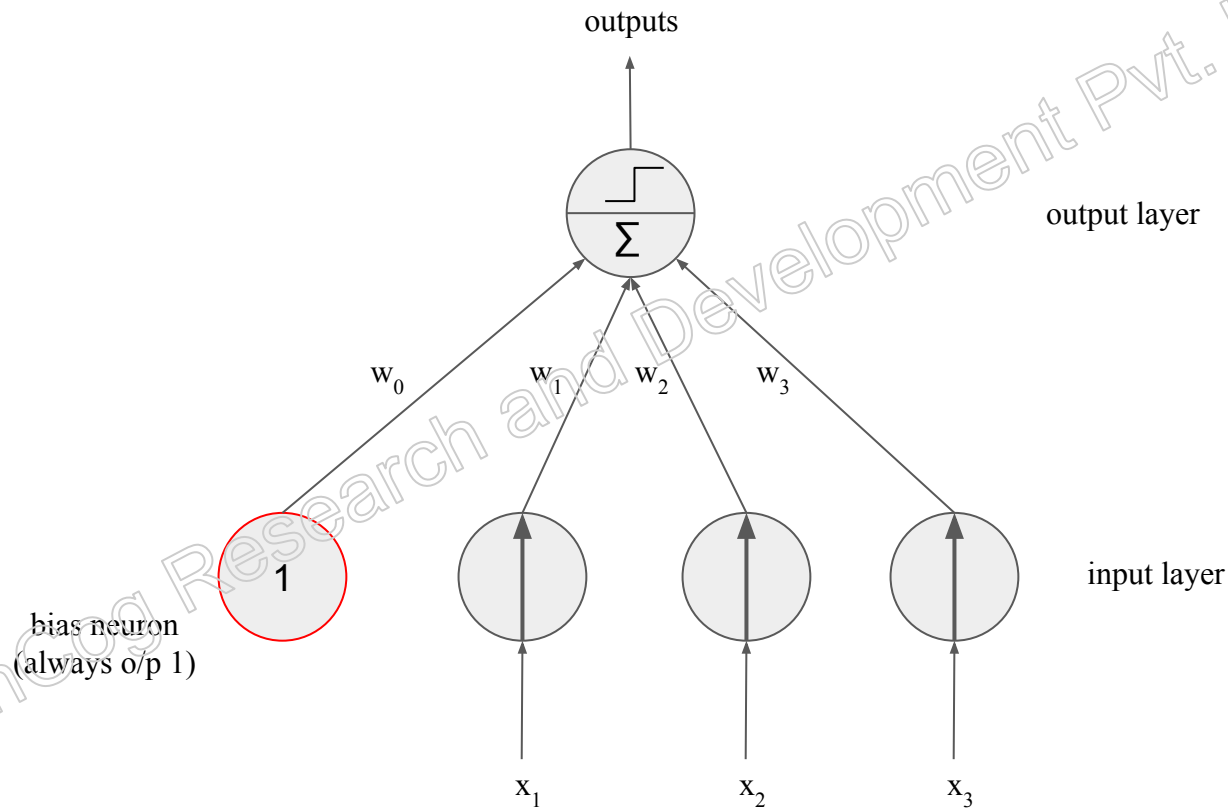
$$\phi(z) = \begin{cases} 1 & \text{if } z \geq 0 \\ -1 & \text{otherwise} \end{cases}$$



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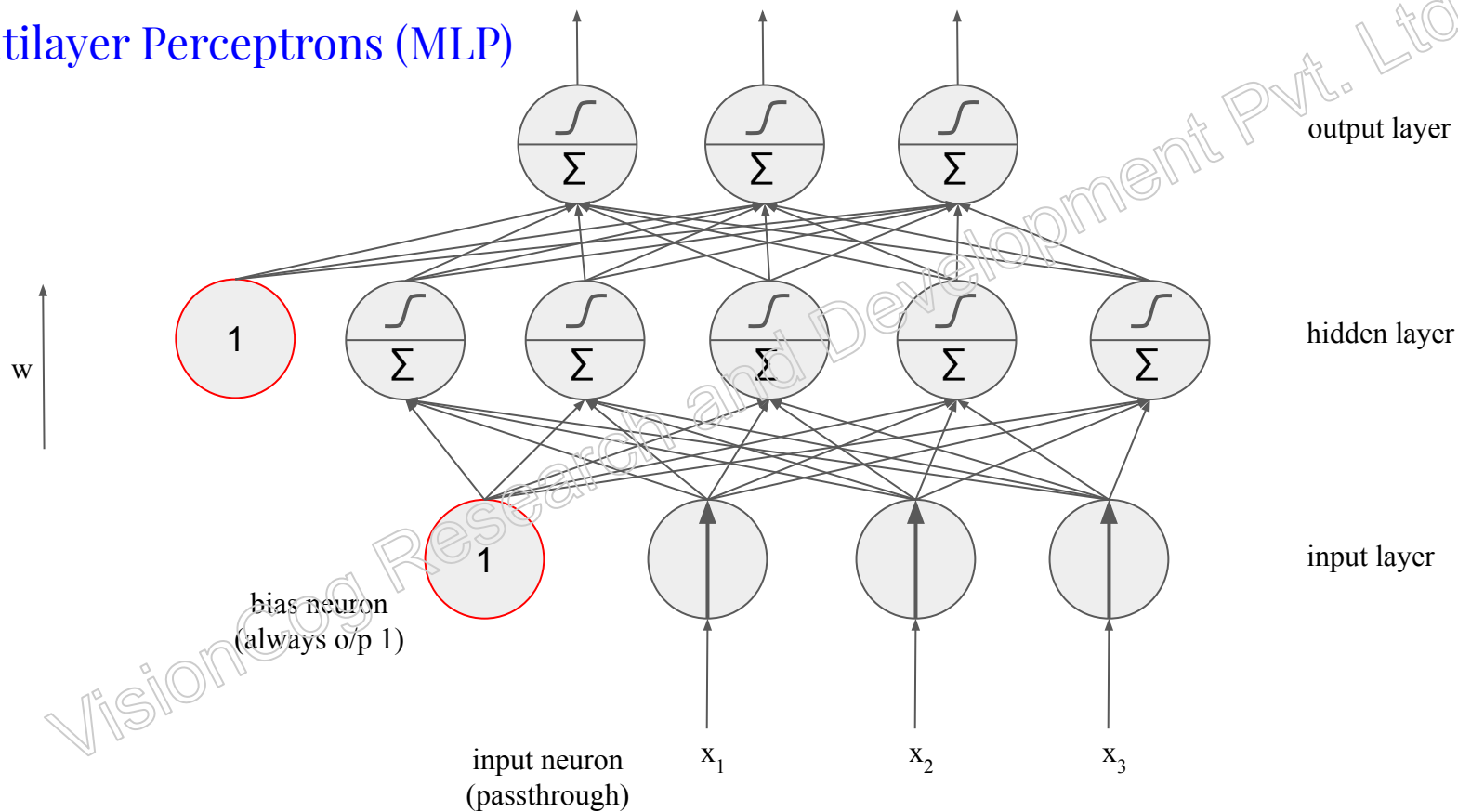
Perceptron



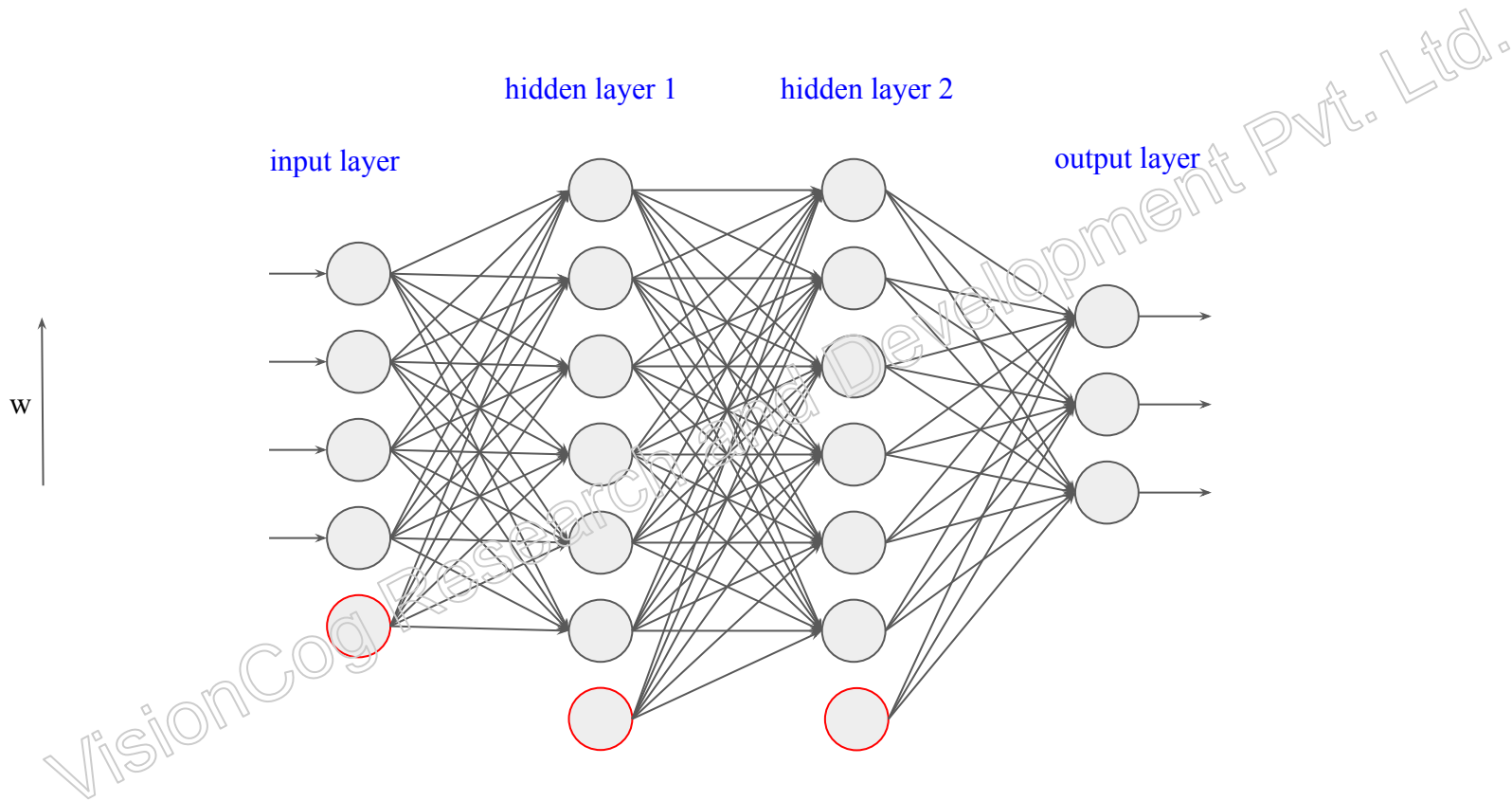
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Multilayer Perceptrons (MLP)



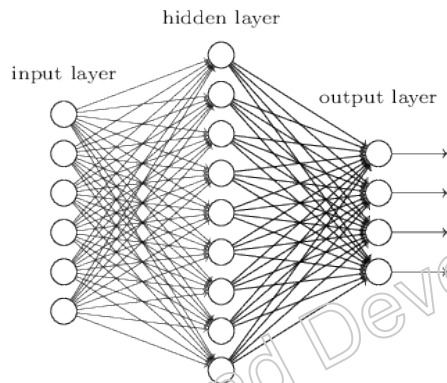
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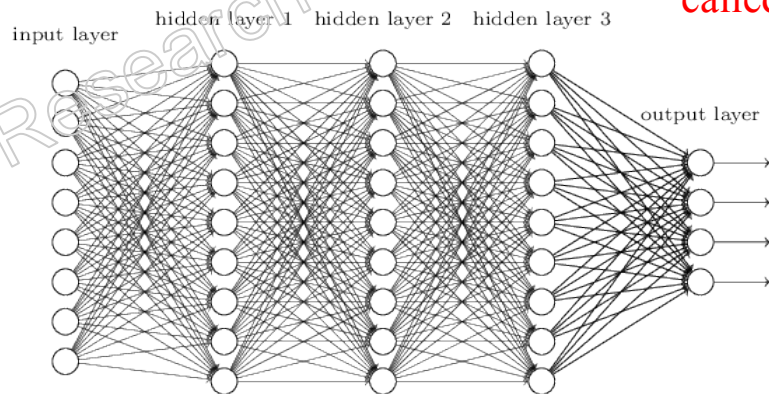


Multilayer Perceptrons (MLP)



When MLP contains *two or more hidden* layers, then such an MLP is called **Deep Neural Network (DNN)**

Deep Neural Network (DNN)





FLOWER CLASSIFICATION

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Flower Classification

daisy



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Flower Classification

dandelion



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Flower Classification

rose



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Flower Classification

sunflower



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Flower Classification

tulip



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http://download.tensorflow.org/example_images/flower_photos.tgz (3,670)

Tiny version

https://www.visioncog.com/rpk/tiny_FR.zip (500)

Flower Classification

(100 each, size of image varies)

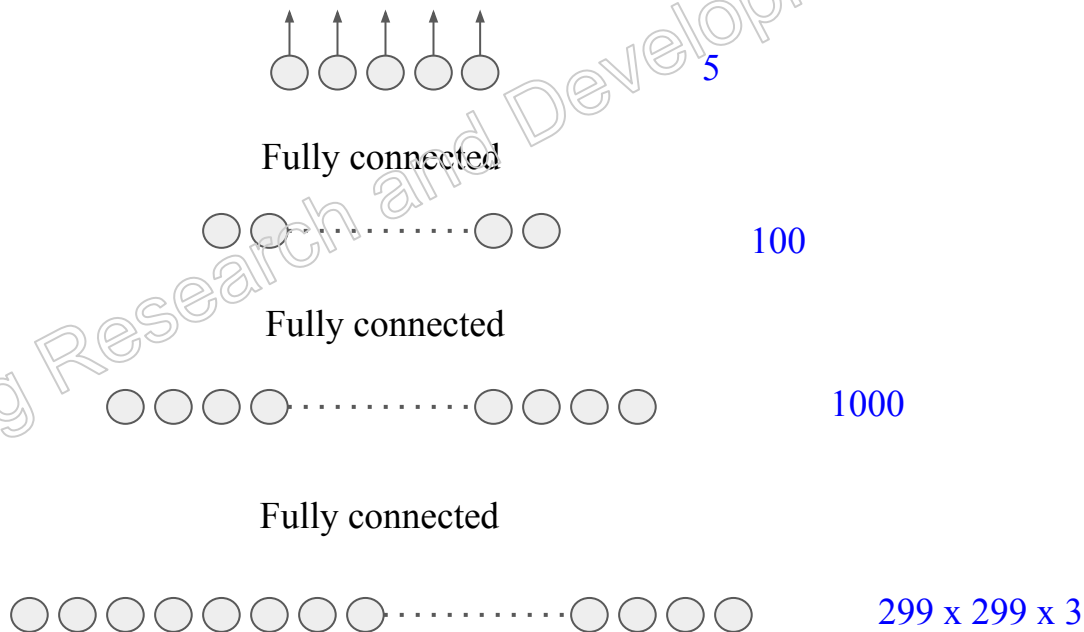
- daisy
- dandelion
- rose
- sunflower
- tulip



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Build a DNN for Flower classification as shown below:



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Original dataset

http://download.tensorflow.org/example_images/flower_photos.tgz

Download tiny version of the dataset from VisionCog website

After download and unzip, remember to comment the following two lines.


```
!wget https://www.visioncog.com/rpk/tiny_FR.zip
```

```
!unzip tiny_FR.zip
```

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- ▶️ sample_data
- ▶️ tiny_FR
- 📄 tiny_FR.zip

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Original dataset

http://download.tensorflow.org/example_images/flower_photos.tgz

Download tiny version of the dataset from VisionCog website

After download and unzip, remember to comment the following two lines.

#!/wget https://www.visioncog.com/rpk/tiny_FR.zip

#!/unzip tiny_FR.zip

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```
# Install TensorFlow
try:
    # %tensorflow_version only exists in Colab.
    %tensorflow_version 2.x
except Exception:
    pass

import tensorflow as tf
print(tf.__version__)

# TensorFlow 2.x selected.
# 2.0.0-rc1
```

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```
from tensorflow import keras  
tf.random.set_seed(42)
```

```
import numpy as np  
np.random.seed(42)
```

```
import matplotlib.pyplot as plt  
%matplotlib inline
```

```
import glob  
import PIL  
from PIL import Image
```

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```
imgFiles = glob.glob("tiny_FR/*/*.jpg")
```

```
for items in imgFiles[:5]:  
    print(items)
```

```
# tiny_FR/sunflower/1715303025_e7065327e2.jpg  
# tiny_FR/sunflower/2442985637_8748180f69.jpg  
# tiny_FR/sunflower/27466794_57e4fe5656.jpg  
# tiny_FR/sunflower/40411019_526f3fc8d9_m.jpg  
# tiny_FR/sunflower/253586685_ee5b5f5232.jpg
```

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```
X = []
y = []

for fName in imgFiles:

    X_i = Image.open(fName) # tiny_FR/sunflower/1715303025_e7065327e2.jpg (500, 333)

    X_i = X_i.resize((299,299)) # To make them appropriate to Xception model when using Transfer Learning

    X_i = np.array(X_i) / 255.0 # Normalize to range 0.0 to 1.0 (not stretching, only scaling)

    X.append(X_i)

    label = fName.split("/") # ['tiny_FR', 'sunflower', '1715303025_e7065327e2.jpg']

    y_i = label[1] # 'sunflower'

    y.append(y_i)
```

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```
print(set(y))  
# {'daisy', 'sunflower', 'dandelion', 'rose', 'tulip'}
```

```
from sklearn.preprocessing import LabelEncoder
```

```
lEncoder = LabelEncoder()  
y = lEncoder.fit_transform(y)
```

```
print(set(y))  
# {0, 1, 2, 3, 4}
```

```
print(lEncoder.classes_)  
# ['daisy' 'dandelion' 'rose' 'sunflower' 'tulip']
```

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```
X = np.array(X)
```

```
y = np.array(y)
```

```
print(X.shape)
```

(500, 299, 299, 3)

```
print(y.shape)
```

(500,)

```
from sklearn.model_selection import train_test_split
```

[illegible]

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```
print("X_train_shape: {}".format(X_train.shape))
```

```
# X_train_shape: (400, 299, 299, 3)
```

```
print("X_test_shape: {}".format(X_test.shape))
```

```
# X_test_shape: (100, 299, 299, 3)
```

```
# Standard scaling
```

```
mu = X_train.mean()
```

```
std = X_train.std()
```

```
X_train_std = (X_train-mu)/std
```

```
X_test_std = (X_test-mu)/std
```


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Create the network using Functional API method

```
input_ = keras.layers.Input(shape = X_train.shape[1:])
```

```
x = keras.layers.Flatten()(input_)
```

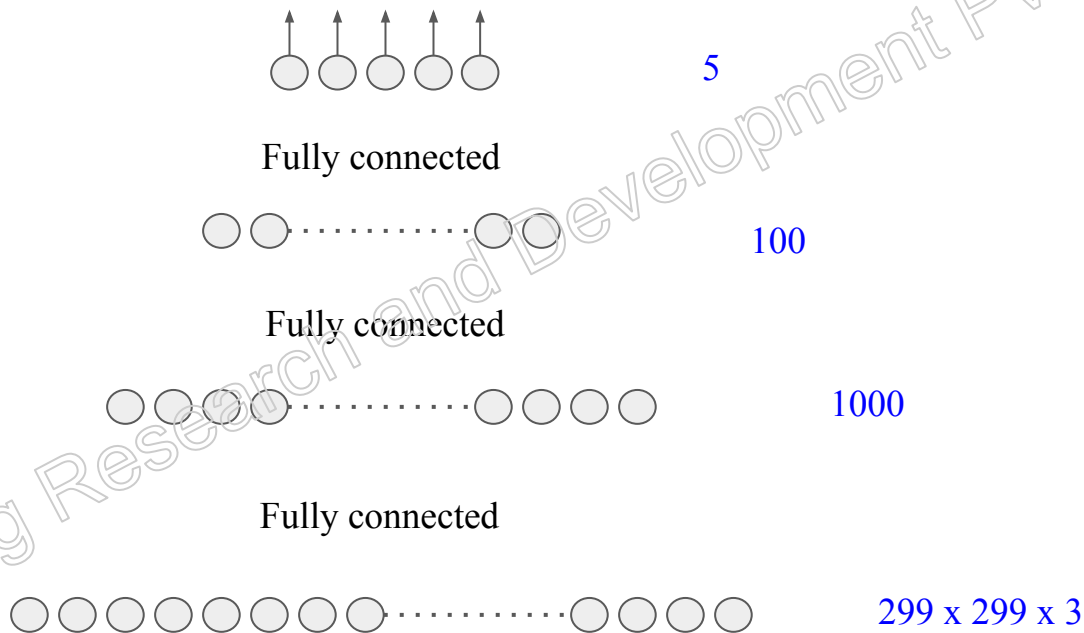
```
x = keras.layers.Dense(units=1000, activation='relu')(x)
```

```
x = keras.layers.Dense(units=100, activation='relu')(x)
```

```
output_ = keras.layers.Dense(units=5, activation='softmax')(x)
```

```
model_DNN = keras.models.Model(inputs=[input_], outputs=[output_])
```

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```
model_DNN.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 299, 299, 3)]	0
flatten (Flatten)	(None, 268203)	0
dense (Dense)	(None, 1000)	268204000
dense_1 (Dense)	(None, 100)	100100
dense_2 (Dense)	(None, 5)	505

Total params: 268,304,605

Trainable params: 268,304,605

Non-trainable params: 0

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```
model_DNN.compile(loss='sparse_categorical_crossentropy',  
                  optimizer='adam', metrics=['accuracy'])
```

```
history_DNN = model_DNN.fit(X_train, y_train, epochs=25,  
                             validation_split=0.1, batch_size=16)
```

Train on 360 samples, validate on 40 samples

Epoch 1/25

360/360 [===]-3s 9ms/sample - loss: 155.1205 - accuracy: 0.2278 - val_loss: 61.1286 - val_accuracy: 0.2750

Epoch 2/25

360/360 [===]-2s 5ms/sample - loss: 30.8947 - accuracy: 0.3750 - val_loss: 23.5717 - val_accuracy: 0.2750

Epoch 3/25

360/360 [===]-2s 5ms/sample - loss: 12.8762 - accuracy: 0.4889 - val_loss: 16.7457 - val_accuracy: 0.4000

...

Epoch 24/25

360/360 [===] - 2s 5ms/sample - loss: 0.4303 - accuracy: 0.9333 - val_loss: 11.7746 - val_accuracy: 0.3750

Epoch 25/25

360/360 [===] - 2s 5ms/sample - loss: 0.1650 - accuracy: 0.9611 - val_loss: 10.3161 - val_accuracy: 0.3250

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Train on 360 samples, validate on 40 samples

Epoch 1/25

360/360 [===]-3s 9ms/sample - loss: 155.1205 - accuracy: 0.2278 - val_loss: 61.1286 - val_accuracy: 0.2750

Epoch 2/25

360/360 [===]-2s 5ms/sample - loss: 30.8947 - accuracy: 0.3750 - val_loss: 23.5717 - val_accuracy: 0.2750

Epoch 3/25

360/360 [===]-2s 5ms/sample - loss: 12.8762 - accuracy: 0.4889 - val_loss: 16.7457 - val_accuracy: 0.4000

...

Epoch 24/25

360/360 [===] - 2s 5ms/sample - loss: 0.4303 - accuracy: 0.9333 - val_loss: 11.7746 - val_accuracy: 0.3750

Epoch 25/25

360/360 [===] - 2s 5ms/sample - loss: 0.1650 - accuracy: 0.9611 - val_loss: 10.3161 - val_accuracy: 0.3250

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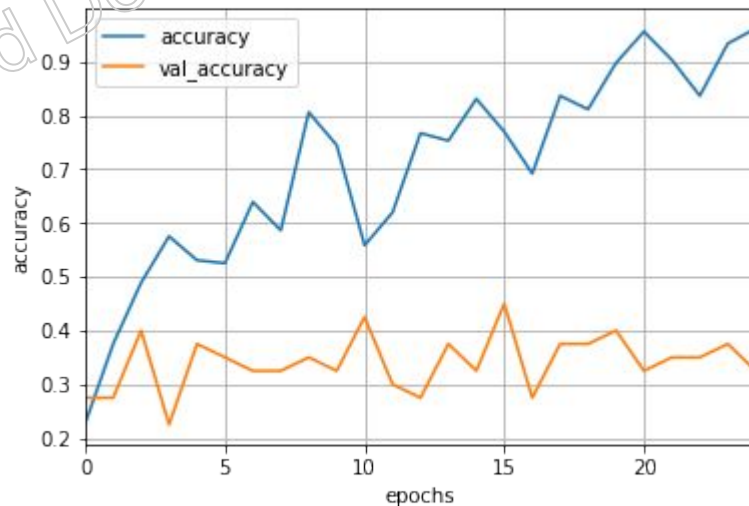


```
keys = ['accuracy', 'val_accuracy']  
progress = {k:v for k,v in history_DNN.history.items() if k in keys}
```

```
import pandas as pd  
pd.DataFrame(progress).plot()
```

```
plt.xlabel("epochs")  
plt.ylabel("accuracy")
```

```
plt.grid(True)  
plt.show()
```



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```
test_loss, test_accuracy = model_DNN.evaluate(X_test, y_test)
# 100/1 [===] - 0s 1ms/sample - loss: 13.9873 - accuracy: 0.3800

print("Test-loss: %f, Test-accuracy: %f" % (test_loss, test_accuracy))
# Test-loss: 12.608617, Test-accuracy: 0.380000
```

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