In [1]:
```
import tensorflow as tf
from tensorflow import keras
```

In [37]:
```
from keras.models import Sequential
from keras.layers import Dense, Activation
model = Sequential([
    Dense (units = 5, input_shape = (3,), activation ='relu'),
    Dense (units = 2, activation ='softmax')
    ])
```

OR we can write following way

In [38]:
```
from keras.models import Sequential
from keras.layers import Dense, Activation
layers = [
    Dense (units = 5, input_shape = (3,), activation ='relu'),
    Dense (units = 2, activation ='softmax')
    ]
model = Sequential(layers)
```

OR we can write following way

In [42]:
```
from keras.models import Sequential
from keras.layers import Dense, Activation
model = Sequential()
model.add(Dense (units = 5, input_shape = (3,), activation ='relu')),
model.add(Dense (units = 2, activation ='softmax'))
```

If one is unsure about the activation function to utilise, just select "RELU", which is a broad activation function that is used in most circumstances these days. ReLU activation function is currently the most commonly used function for the hidden layers (and never for the output layer) for any type of neural network. If the ReLU function does not seem to provide the best results, changing the activation to leaky ReLU might in some cases yield better results and overall performance.

Although the swish activation function does seem to outperform the ReLU function on complex applications, it should be mostly used for only larger neural networks having depths of greater than 50 layers.

If our output layer is meant to be used for binary identification/detection, the sigmoid function is an obvious choice. For binary classification applications, the output (top-most) layer should be activated by the sigmoid function — also for multi-label classification.

The softmax function is always used for multi-class classification applications since it results in the output probabilities of each of the 'k' number of classes in the application which all adds upto 1.

The linear activation function should only be used in the output layer of a simple regression neural network.

For recurrent neural networks (RNNs) the tanh activation function is preferred for the hidden layer(s). It is set by default in TensorFlow.

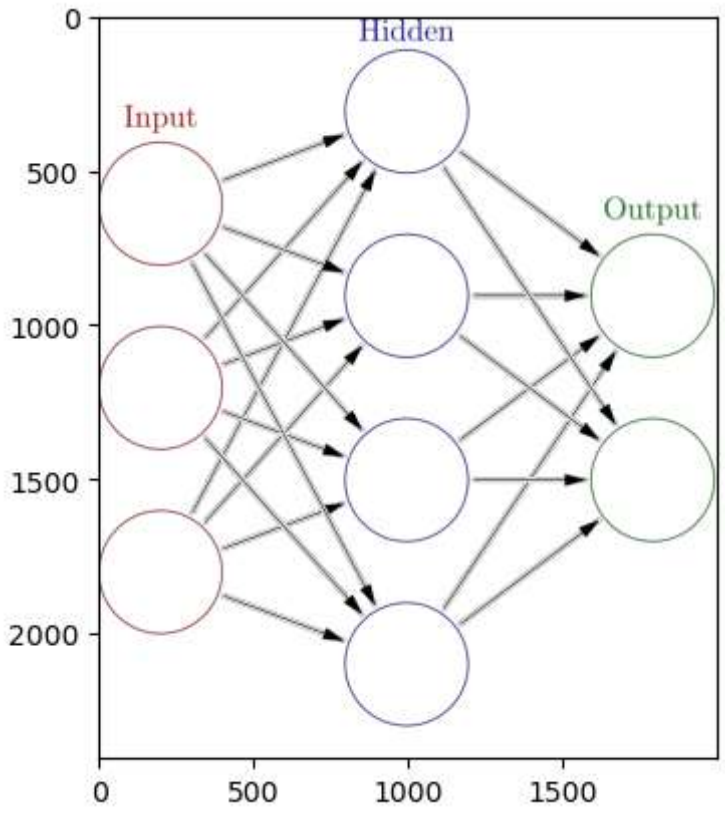
In [33]:
```
a=np.array([0,0,1,1,1,1,1,1,1,1])
print(a.shape)
b=np.array([2.3,1.1])
print(b.shape)
```

```
(10,)
(2,)
```

In [18]:
```
import numpy as  np
from scipy import *
import matplotlib.pyplot as plt
%matplotlib inline
import imageio
img = np.expand_dims(imageio.imread("neural_network.png"),0)
plt.imshow(img[0])
```

```
C:\Users\shalini193091\.conda\envs\tf\lib\site-packages\ipykernel_launcher.py:6: Depr
ecationWarning: Starting with ImageIO v3 the behavior of this function will switch to
that of iio.v3.imread. To keep the current behavior (and make this warning dissapear)
use `import imageio.v2 as imageio` or call `imageio.v2.imread` directly.
```

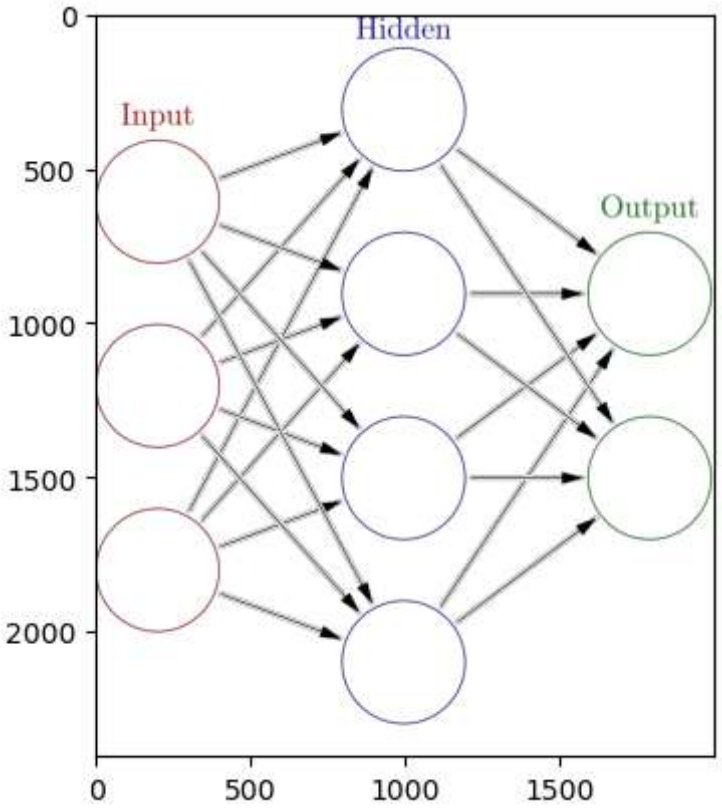
Out[18]:
```
<matplotlib.image.AxesImage at 0x1ec23a231c8>
```



In [28]:
```
import matplotlib.image as mpimg
#fig=plt.figure(figsize=(8,6),dpi=500)
```

```
img = mpimg.imread("neural_network.png")
plt.imshow(img)
```

Out[28]:
```
<matplotlib.image.AxesImage at 0x1ec27e5b348>
```



In [43]:
```
# from PIL import Image
# Open the image form working directory
image = Image.open("neural_network.png")
# summarize some details about the image
print(image.format)
print(image.size)
print(image.mode)
# show the image
image.show()
```

```
PNG
(2000, 2405)
RGBA
```

Why Loss Function is important?

Famous author Peter Druker says You can't improve what you can't measure. That's why the loss function comes into the picture to evaluate how well your algorithm is modeling your dataset.

If the value of the loss function is lower then it's a good model otherwise, we have to change the parameter of the model and minimize the loss.

Loss function vs Cost function

Most people confuse loss function and cost function. let's understand what is loss function and cost function. Cost function and Loss function are synonymous and used interchangeably but they are different.

Loss Function:

A loss function/error function is for a single training example/input.

Cost Function:

A cost function, on the other hand, is the average loss over the entire training dataset.

Loss function in Deep Learning

1. Regression

a. MSE(Mean Squared Error)

b. MAE(Mean Absolute Error)

c. Hubber loss

1. Classification

a. Binary cross-entropy (binary classification)

b. Categorical cross-entropy (multi class classification)

c. Sparse Categorical cross-entropy (If target column has One hot encoding to classes like 0 0 1, 0 1 0, 1 0 0 then use categorical cross-entropy. And if the target column has Numerical encoding to classes like 1,2,3,4….n then use sparse categorical cross-entropy). Sparse categorical cross-entropy faster than Categorical cross-entropy.

1. AutoEncoder

a. KL Divergence

1. GAN

a. Discriminator loss

b. Minmax GAN loss

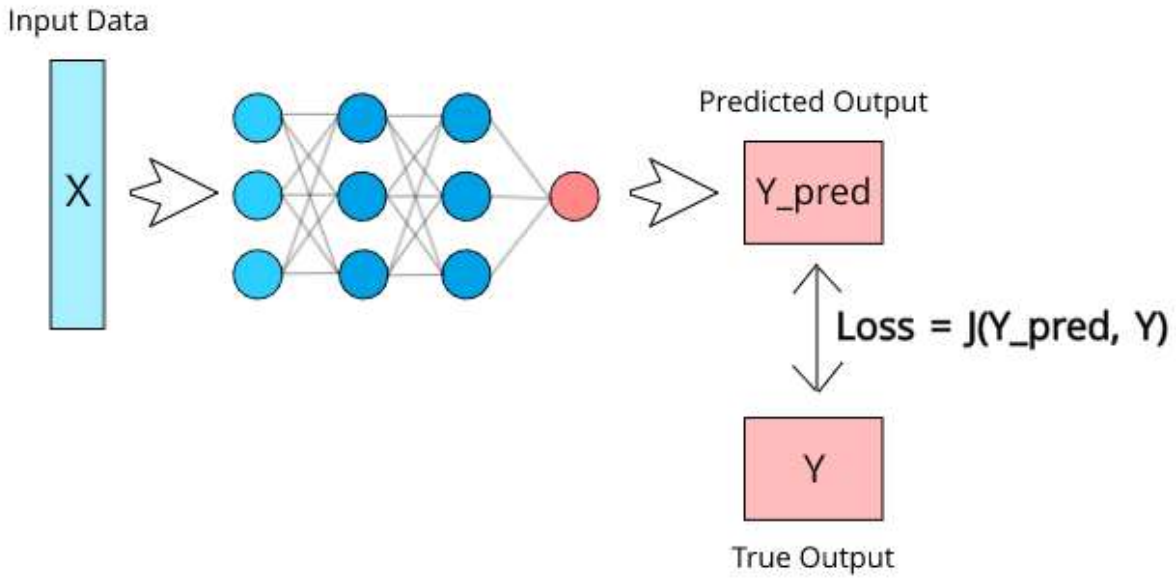
1. Object detection

a. Focal loss

6.Word embeddings

a. Triplet loss

Loss Function



In [1]:
```
import keras
from keras.models import Sequential
from keras.layers import Activation
from keras.layers.core import Dense
from keras.optimizers import Adam
from keras.metrics import categorical_crossentropy
```

In [2]:
```
model = Sequential([
    Dense(units=16, input_shape=(1,), activation='relu'),
    Dense(units=32, activation='relu'),
    Dense(units=2, activation='sigmoid')
])
```

In [3]:
```
model.compile(
    optimizer=Adam(learning_rate=0.0001),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

In [13]:
```
import numpy as np
from random import randint
from sklearn.preprocessing import MinMaxScaler
train_labels = []
train_samples = []

for i in range (1000):
    random_younger = randint (13,64)
    train_samples.append(random_younger)
    train_labels.append(0)

    random_older = randint (65,100)
```

```
    train_samples.append(random_older)
    train_labels.append(1)

for i in range (50):
    random_younger = randint (13,64)
    train_samples.append(random_younger)
    train_labels.append(1)

    random_older = randint (65,100)
    train_samples.append(random_older)
    train_labels.append(0)

#print raw data
for i in train_samples:
    print (i)

train_labels = np.array (train_labels)
train_samples = np.array (train_samples)

scaler = MinMaxScaler(feature_range = (0,1))
scaled_train_samples = scaler.fit_transform ((train_samples).reshape(-1,1))
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In [14]:
```
model.fit(
    x=scaled_train_samples,
    y=train_labels,
    batch_size=10,
    epochs=20,
    shuffle=True,
    verbose=2
)
```

```
Epoch 1/20
210/210 - 1s - loss: 0.6937 - accuracy: 0.4124 - 797ms/epoch - 4ms/step
Epoch 2/20
210/210 - 0s - loss: 0.6729 - accuracy: 0.6138 - 215ms/epoch - 1ms/step
Epoch 3/20
210/210 - 0s - loss: 0.6436 - accuracy: 0.7462 - 199ms/epoch - 948us/step
Epoch 4/20
210/210 - 0s - loss: 0.6164 - accuracy: 0.7695 - 183ms/epoch - 870us/step
Epoch 5/20
210/210 - 0s - loss: 0.5893 - accuracy: 0.8000 - 219ms/epoch - 1ms/step
Epoch 6/20
210/210 - 0s - loss: 0.5606 - accuracy: 0.8138 - 189ms/epoch - 900us/step
Epoch 7/20
210/210 - 0s - loss: 0.5309 - accuracy: 0.8386 - 185ms/epoch - 883us/step
Epoch 8/20
210/210 - 0s - loss: 0.5007 - accuracy: 0.8452 - 188ms/epoch - 897us/step
Epoch 9/20
210/210 - 0s - loss: 0.4712 - accuracy: 0.8705 - 179ms/epoch - 854us/step
Epoch 10/20
210/210 - 0s - loss: 0.4432 - accuracy: 0.8714 - 201ms/epoch - 956us/step
Epoch 11/20
210/210 - 0s - loss: 0.4170 - accuracy: 0.8857 - 234ms/epoch - 1ms/step
Epoch 12/20
210/210 - 0s - loss: 0.3929 - accuracy: 0.9043 - 245ms/epoch - 1ms/step
Epoch 13/20
210/210 - 0s - loss: 0.3717 - accuracy: 0.9076 - 268ms/epoch - 1ms/step
Epoch 14/20
210/210 - 0s - loss: 0.3537 - accuracy: 0.9090 - 198ms/epoch - 941us/step
Epoch 15/20
210/210 - 0s - loss: 0.3386 - accuracy: 0.9148 - 197ms/epoch - 937us/step
Epoch 16/20
210/210 - 0s - loss: 0.3259 - accuracy: 0.9190 - 185ms/epoch - 881us/step
Epoch 17/20
210/210 - 0s - loss: 0.3154 - accuracy: 0.9214 - 196ms/epoch - 931us/step
Epoch 18/20
210/210 - 0s - loss: 0.3067 - accuracy: 0.9190 - 201ms/epoch - 958us/step
Epoch 19/20
210/210 - 0s - loss: 0.2994 - accuracy: 0.9281 - 231ms/epoch - 1ms/step
Epoch 20/20
210/210 - 0s - loss: 0.2934 - accuracy: 0.9238 - 234ms/epoch - 1ms/step
```

Out[14]:
```
<keras.callbacks.History at 0x1d0f9136cc8>
```

In [ ]: