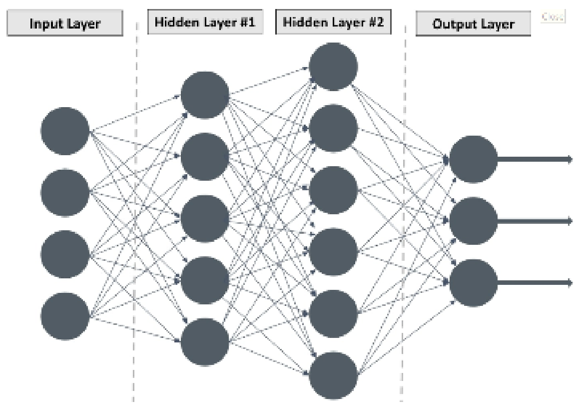
Author: Toufiq Musah, [https://github.com/toufiqmusah (https://github.com/toufiqmusah)](https://github.com/toufiqmusah)

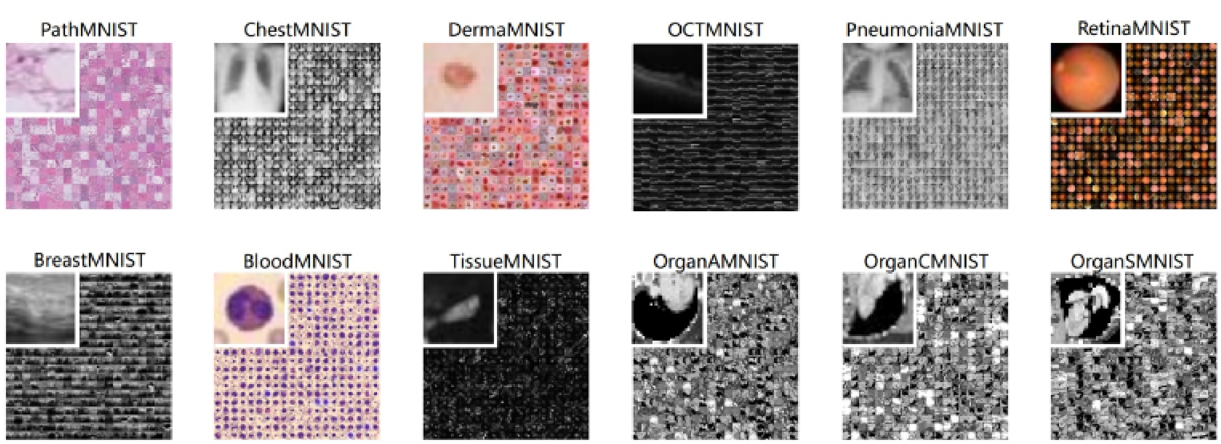
WHAT IS THE ML/DL WORKFLOW?

1. Define your problem. Is it relevant to Machine Learning(Data Related)
2. Gather and prepare your dataset.
3. Select the right model for the job. Will it be a Deep Learning(DL) or Machine Learning(ML) model.
4. Train your model on the dataset, and perform validation.
5. Fine-Tune your model to get better results(Will you need to expand the dataset and retrain? Do some hyperparameters need to change?)
6. Deploy your solution.



WHAT IS OUR WORKFLOW TODAY?

1. Cases of pneumonia are on the rise, and the clinicians are swamped with too many cases to assess and diagnosis. Why not help them automate the process a little?
2. We will gather a dataset of chest x-rays of patients with and without pneuomonia. Luckily, a public dataset called the [MedMNIST (https://medmnist.com/)](https://medmnist.com/) already contains that.The data preparation task can be a little tough.
3. Since it is an image related task, we will go with a Deep Learning approach. Specifically using Convolutional Neural Networks(CNNs)
4. We will define our CNN with its various layers and set it up to perform image classification and classify pneumonia x-ray scans from non-pneumonia ones.
5. Based on the performance of the model, the model will be optimised, fine-tuned and saved.



Data Acquisition and Exploration

In [4]:
```
#Let's start by importing some of the necessary libraries for the job at hand.
#We will be using the TensorFlow & Keras Libraries for this endeavour.
# I often prefer PyTorch for computer vision tasks like this, but TensorFlow can be more beginner frie
ndly.

import numpy as np # To load and manipulate numerical data
import matplotlib.pyplot as plt # To plot images, etc

import tensorflow as tf
from tensorflow.keras.utils import to_categorical # To perform One-hot encoding
from tensorflow.keras import layers, models, Model
```

In [5]:
```
# The MedMNIST dataset we wish to use exists as a library we can install and use.
# This means that we don't have to manually download and import the data into the notebook
# Do note that it is not always this easy

!pip -q install medmnist
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 88.4/88.4 kB 5.3 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
  Building wheel for fire (setup.py) ... done
```

In [6]:
```
# We will import the medmnist library and look at the available datasets
# Note that I read the documentation on MedMNIST before knowing how to use it
# Lesson of the story: READ DOCUMENTATION!!!

import medmnist

!python -m medmnist available
```

```
MedMNIST v3.0.1 @ https://github.com/MedMNIST/MedMNIST/
All available datasets:
        pathmnist       | PathMNIST       | Size: 28 (default), 64, 128, 224.
        chestmnist      | ChestMNIST      | Size: 28 (default), 64, 128, 224.
        dermamnist      | DermaMNIST      | Size: 28 (default), 64, 128, 224.
        octmnist        | OCTMNIST        | Size: 28 (default), 64, 128, 224.
        pneumoniamnist  | PneumoniaMNIST  | Size: 28 (default), 64, 128, 224.
        retinamnist     | RetinaMNIST     | Size: 28 (default), 64, 128, 224.
        breastmnist     | BreastMNIST     | Size: 28 (default), 64, 128, 224.
        bloodmnist      | BloodMNIST      | Size: 28 (default), 64, 128, 224.
        tissuemnist     | TissueMNIST     | Size: 28 (default), 64, 128, 224.
        organamnist     | OrganAMNIST     | Size: 28 (default), 64, 128, 224.
        organcmnist     | OrganCMNIST     | Size: 28 (default), 64, 128, 224.
        organsmnist     | OrganSMNIST     | Size: 28 (default), 64, 128, 224.
        organmnist3d    | OrganMNIST3D    | Size: 28 (default), 64.
        nodulemnist3d   | NoduleMNIST3D   | Size: 28 (default), 64.
        adrenalmnist3d  | AdrenalMNIST3D  | Size: 28 (default), 64.
        fracturemnist3d | FractureMNIST3D | Size: 28 (default), 64.
        vesselmnist3d   | VesselMNIST3D   | Size: 28 (default), 64.
        synapsemnist3d  | SynapseMNIST3D  | Size: 28 (default), 64.
```

In [7]:
```
# Let's Download the Pneumonia training and testing dataset for the task

data_path = '/content/' # The path the dataset will be downloaded into.

train_dataset = medmnist.PneumoniaMNIST(split = 'train', download = True, size = 128, root = data_pat
h)
test_dataset = medmnist.PneumoniaMNIST(split = 'test', download = True, size = 128, root = data_path)
```

```
Downloading https://zenodo.org/records/10519652/files/pneumoniamnist_128.npz?download=1 to /content/p
neumoniamnist_128.npz

100%|██████████| 75506212/75506212 [00:00<00:00, 116997600.18it/s]

Using downloaded and verified file: /content/pneumoniamnist_128.npz
```

In [8]:
```
#Now that the dataset has been downloaded, let's load it with numpy and see what it contains
# The dataset we have is already split into the training, validation and testing.
# This is not always the case

data = np.load('/content/pneumoniamnist_128.npz')
data.files
```

Out[8]:
```
['train_images',
 'train_labels',
 'val_images',
 'val_labels',
 'test_images',
 'test_labels']
```

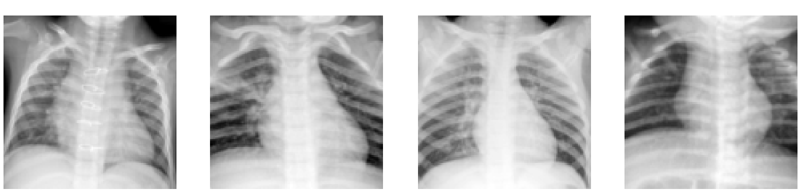
In [9]:
```
data['train_images'].shape
```

Out[9]:
```
(4708, 128, 128)
```

In [10]:
```
plt.imshow(data['train_images'][0], cmap = 'gray')
plt.axis('off')
```

Out[10]:
```
(-0.5, 127.5, 127.5, -0.5)
```

In [11]:
```
# Let's see what the images look like using the Matplotlib library - plt

plt.subplot(1, 4, 1)
plt.imshow(data['train_images'][0], cmap = 'gray')
plt.axis('off')
plt.subplot(1, 4 ,2)
plt.imshow(data['train_images'][1], cmap = 'gray')
plt.axis('off')
plt.subplot(1, 4, 3)
plt.imshow(data['train_images'][2], cmap = 'gray')
plt.axis('off')
plt.subplot(1, 4, 4)
plt.imshow(data['train_images'][10], cmap = 'gray')
plt.axis('off')
plt.show()
```



Data Preparation Stage Begins

In [12]:
```
# We will create our training, validation and testing split variables below
# The test split is not always necessary though

(train_images, train_labels) = (data['train_images'], data['train_labels'])
(val_images, val_labels) = (data['val_images'], data['val_labels'])
(test_images, test_labels) = (data['test_images'], data['test_labels'])

# We will continue by normalising the images. i.e [0, 255] -> [0, 1]
train_images = train_images.astype('float32') / 255.0
val_images = val_images.astype('float32') / 255.0
test_images = test_images.astype('float32') / 255.0

# Let's reshape the images so they can fit well into the model later
# Going from: [Batch, Height, Width] -> [Batch, Height, Width, Channels]
train_images = tf.reshape(train_images, (-1, 128, 128, 1))
val_images = tf.reshape(val_images, (-1, 128, 128, 1))
test_images = tf.reshape(test_images, (-1, 128, 128, 1))

# Let's one-hot encode the labels (Removes ordinality, and can improve model performance)
train_labels = to_categorical(train_labels)
val_labels = to_categorical(val_labels)
test_labels = to_categorical(test_labels)
```

In [13]:
```
train_images.shape
```

Out[13]:
```
TensorShape([4708, 128, 128, 1])
```

In [14]:
```
# Notice that the images will still look same after normalising.

plt.imshow(train_images[0], cmap = 'gray')
plt.axis('off')
```

Out[14]:
```
(-0.5, 127.5, 127.5, -0.5)
```

In [15]:
```
# We are in the endgame of data preprocessing now.
# Let's convert the numpy data into the right format for trainining on TensorFlow (i.e Tensors)

train_dataset = tf.data.Dataset.from_tensor_slices((train_images, train_labels))
val_dataset = tf.data.Dataset.from_tensor_slices((val_images, val_labels))
test_dataset = tf.data.Dataset.from_tensor_slices((test_images, test_labels))
# We call them "train_dataset, etc" because they contains both the images and labels
```

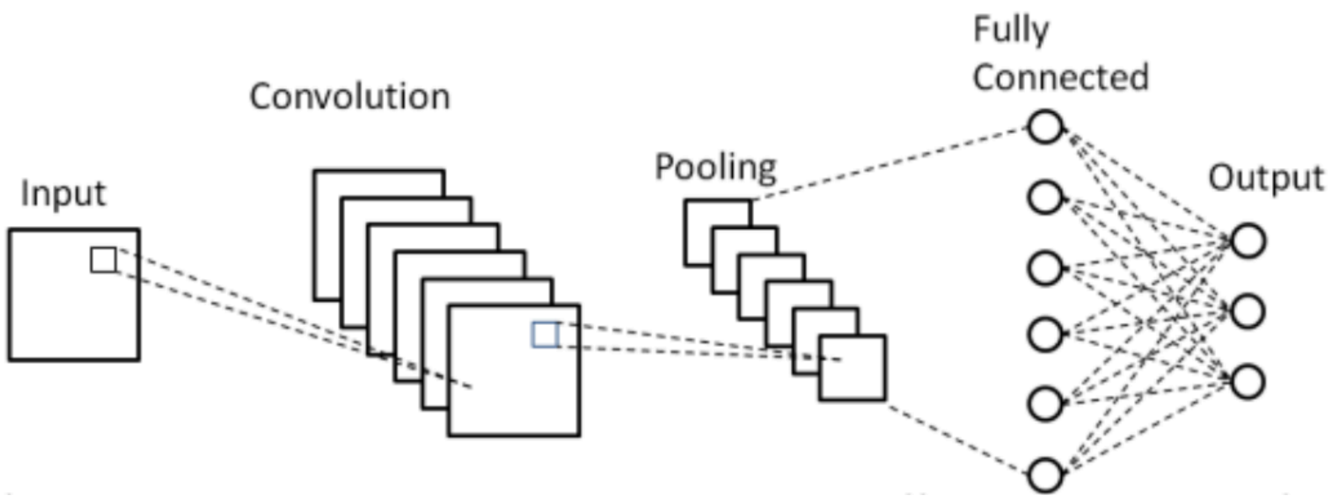
In [16]:
```python
# We will continue by shuffling and the batching dataset
# Batching ensure that the model trains on a subset of the dataset at a time
# This is important to reduce computational costs, as well as prevent overfitting

train_dataset = train_dataset.shuffle(buffer_size = 1024).batch(batch_size = 64)
val_dataset = val_dataset.batch(batch_size = 64)
test_dataset = test_dataset.batch(batch_size = 64)

train_dataset
```

Out[16]:
```
<_BatchDataset element_spec=(TensorSpec(shape=(None, 128, 128, 1), dtype=tf.float32, name=None), Tens
orSpec(shape=(None, 2), dtype=tf.float64, name=None))>
```

Model Implementation

Remember that since it is an (computer vision)/(imaging) task, we chose to go with a deep learning model. Particularly, the Convolutional Neural Network (CNN). The CNN is made up of 3 main types of layers.

- Convolutional Layer: To detect features and patterns in images
- Pooling Layer: To remove complexities and extract dominant features
- Dense(Linear) Layer: To perform classification based on the extracted features
- We also have dropout layers which reduce overfitting, and activation functions that introduce non-linearity. Non-Linearity allows use to work with very complex data.



In [17]:
```
# Finally done with image preprocessing. That wasn't fun at all.
# Let's get to the exciting part and make that model.
# We are going to implement a TensorFlow Sequential model.


model = tf.keras.models.Sequential([
    # Note the input shape is the desired size of the image 128x128 with 1, representing grayscale col
or
    # This is the first convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu', input_shape=(128, 128, 1)),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The second convolution
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The third convolution
    tf.keras.layers.Conv2D(256, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The fourth convolution
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.GlobalAveragePooling2D(),
    # Flatten the results to feed into a Dense Layer
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dropout(0.5),
    # 512 neuron hidden layer
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(2, activation='softmax')
    # We use softmax because the labels were One-hot encoded.
    # Otherwise, this is a binary classifcation task, and the activation will have been 'sigmoid'.
])

model.summary() # This will give us a brief summary of the model, showing how features move from one l
ayer to another.
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 64)	640
max_pooling2d (MaxPooling2D)	(None, 63, 63, 64)	0
conv2d_1 (Conv2D)	(None, 61, 61, 128)	73,856
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_2 (Conv2D)	(None, 28, 28, 256)	295,168
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 256)	0
conv2d_3 (Conv2D)	(None, 12, 12, 128)	295,040
global_average_pooling2d (GlobalAveragePooling2D)	(None, 128)	0
flatten (Flatten)	(None, 128)	0
dropout (Dropout)	(None, 128)	0
dense (Dense)	(None, 512)	66,048
dense_1 (Dense)	(None, 2)	1,026

Total params: 731,778 (2.79 MB)

Trainable params: 731,778 (2.79 MB)

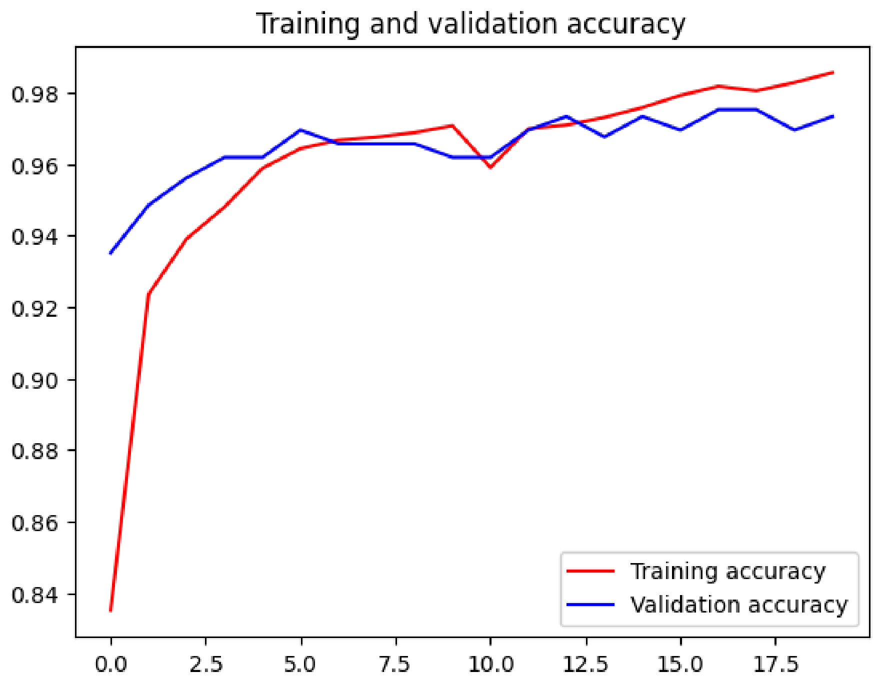
Non-trainable params: 0 (0.00 B)

Model Training and Evaluation

In [76]:
```
# We will now define the hyperparameters with which our model will learn with.
# In the model.comnpile phase; we select a loss function (which helps the model know how right or wron
g its is),
# the optimizer will update the weights of the neural network based on the loss,
# and metrics, which tells the model what metrics to prioritise in the learning process.

# In the model.fit phase, we parse the training and validation datasets,
# as well as setting an epoch count which tells the model how many times to iterate over the entire da
taset

model.compile(loss = 'binary_crossentropy', optimizer='adam', metrics=['accuracy'])
history = model.fit(train_dataset, epochs=10, validation_data = val_dataset, verbose = 1)

model.save('Pneumonia-Model.keras')
```

```
Epoch 1/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 10s 92ms/step - accuracy: 0.9381 - loss: 0.1571 - val_accuracy: 0.9447 - v
al_loss: 0.1348
Epoch 2/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 61ms/step - accuracy: 0.9416 - loss: 0.1561 - val_accuracy: 0.9313 - va
l_loss: 0.1612
Epoch 3/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 62ms/step - accuracy: 0.9497 - loss: 0.1265 - val_accuracy: 0.9504 - va
l_loss: 0.1402
Epoch 4/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 61ms/step - accuracy: 0.9545 - loss: 0.1239 - val_accuracy: 0.9447 - va
l_loss: 0.1455
Epoch 5/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 63ms/step - accuracy: 0.9537 - loss: 0.1226 - val_accuracy: 0.9485 - va
l_loss: 0.1347
Epoch 6/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 61ms/step - accuracy: 0.9492 - loss: 0.1210 - val_accuracy: 0.9389 - va
l_loss: 0.1526
Epoch 7/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 62ms/step - accuracy: 0.9473 - loss: 0.1277 - val_accuracy: 0.8969 - va
l_loss: 0.2029
Epoch 8/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 62ms/step - accuracy: 0.9560 - loss: 0.1219 - val_accuracy: 0.9141 - va
l_loss: 0.1735
Epoch 9/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 64ms/step - accuracy: 0.9516 - loss: 0.1260 - val_accuracy: 0.9447 - va
l_loss: 0.1295
Epoch 10/10
74/74 ━━━━━━━━━━━━━━━━━━━━ 5s 62ms/step - accuracy: 0.9581 - loss: 0.1095 - val_accuracy: 0.9389 - va
l_loss: 0.1404
```

In [16]:
```python
# How did the model perform in training and validation?

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'r', label='Training accuracy')
plt.plot(epochs, val_acc, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend(loc=0)
plt.figure()

plt.show()
```




```
<Figure size 640x480 with 0 Axes>
```

Explainability

How would we know if our model is learning using the right features?
Are the feeatures clinically relevant? Can we somewhat trust this model?

The best answer to all of this is Explainable AI. Maybe in another notebook in the future

References

1. https://medmnist.com/ (https://medmnist.com/)
2. Tensorflow Zero to Hero: https://youtube.com/playlist?list=PLQY2H8rRoyvwWuPiWnuTDBHe7I0fMSsfO&si=kwRugxgtYSgrECYV (https://youtube.com/playlist?list=PLQY2H8rRoyvwWuPiWnuTDBHe7I0fMSsfO&si=kwRugxgtYSgrECYV)