Breast Cancer Detection

GROUP NO. 3

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Objectives

- To classify the tumors as Benign and Malignant tumors.
- To detect location of the tumour.
- To automate the process of detection of abnormal tissues.
- To evaluate the performance of various Deep Learning approaches for detection and segmentation of tumours

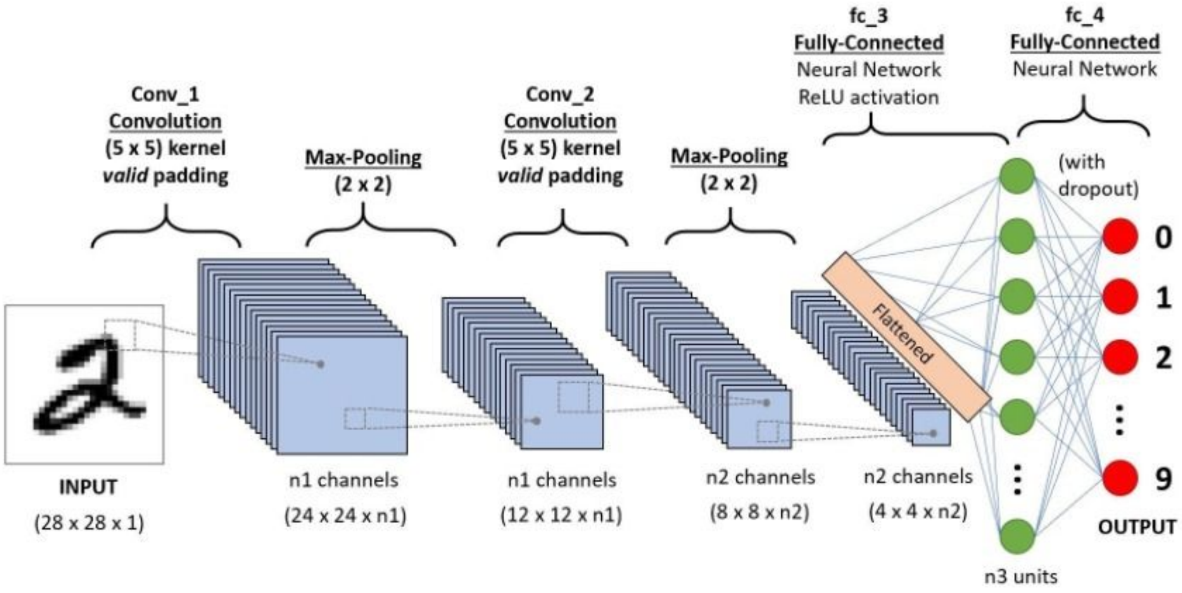
Outcomes

- Software tool which automatically detects cancerous tissues.
- Software will be able to identify location of tumour and detect volume of tumour.
- It will act an an assisting tool to radiologists to classify or choose the abnormal mammogram and prioritise based on level of concern.
- Learning how to write a Technical paper using LaTeX

Problem Statement

To develop an automated detection and segmentation of tumours using mammogram in Cranial-Caudal and Medial-lateral oblique (CC and MLO) views using Deep Learning Techniques

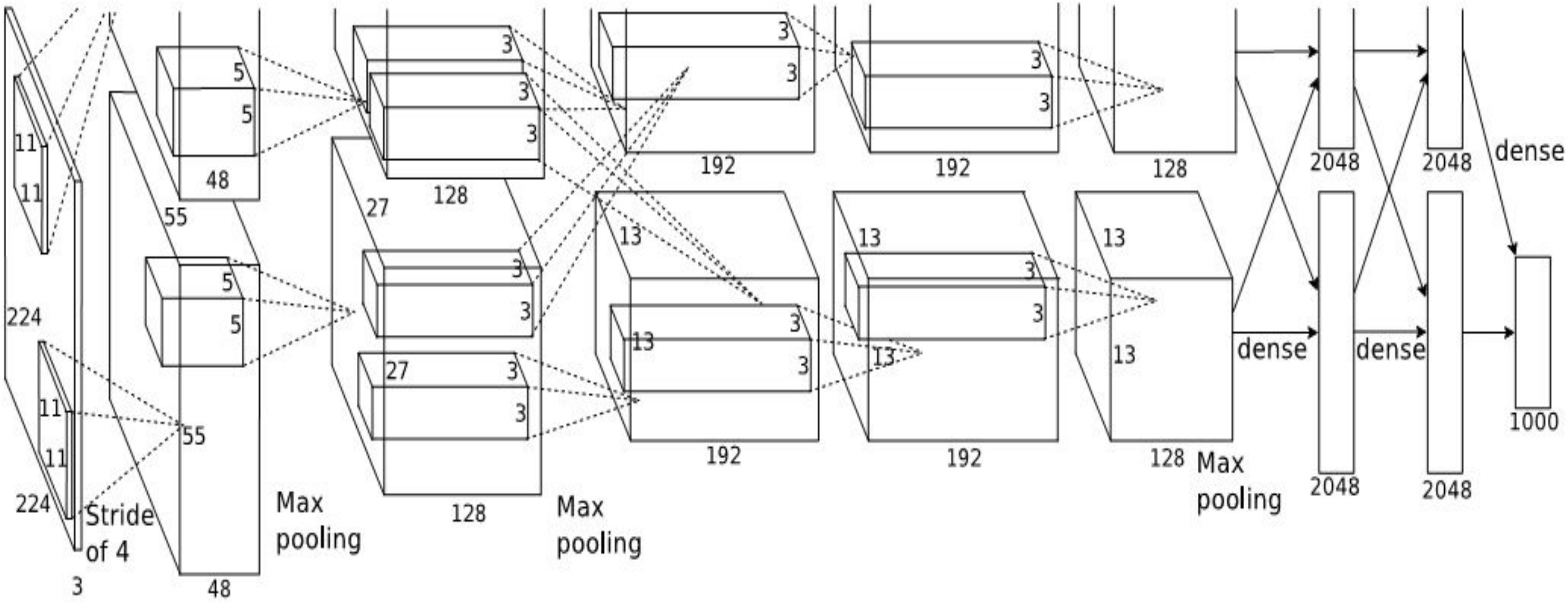
CNN


Conv_1
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
Conv_2
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
fc_3
Fully-Connected
Neural Network
ReLU activation
fc_4
Fully-Connected
Neural Network
(with
dropout)
Flattened
0
1
2
9
INPUT
(28 x 28 x 1)
n1 channels
(24 x 24 x n1)
n1 channels
(12 x 12 x n1)
n2 channels
(8 x 8 x n2)
n2 channels
(4 x 4 x n2)
n3 units
OUTPUT

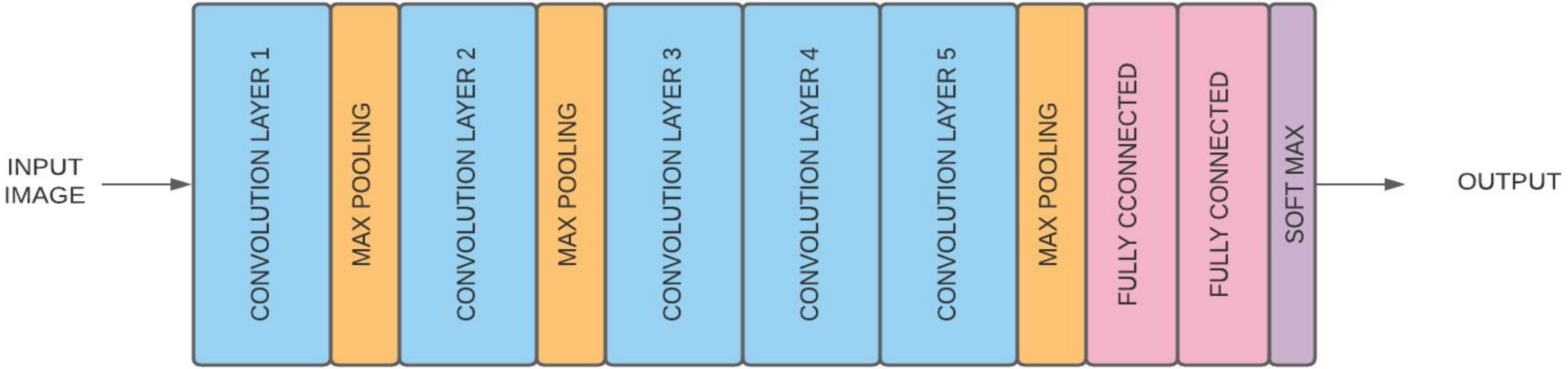
Training Using Alexnet

- 8 layers deep neural network
- A total of 60 million parameters
- 5 Convolutional layers and 3 Fully Connected (dense) layers
- Dataset consisting of 15 million images,over 22,000 categories with variable resolution images so scaled down to fixed resolution 256x256
- Why ReLu Non-linearity?

Architecture of Alexnet



Architecture



Results of Alexnet

+ Code + Text RAM Disk Editing

```
steps_per_epoch=int(8000/32),
epochs=15,
validation_data=test_set,
validation_steps=200,
#callbacks=callback
)
```

```
Found 20000 images belonging to 2 classes.
Found 5000 images belonging to 2 classes.
Epoch 1/5
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:720: UserWarning: This ImageDataGenerator specifies `featurewi
  warnings.warn('This ImageDataGenerator specifies '
/usr/local/lib/python3.6/dist-packages/keras_preprocessing/image/image_data_generator.py:728: UserWarning: This ImageDataGenerator specifies `featurewi
  warnings.warn('This ImageDataGenerator specifies '
250/250 [==============================] - 109s 437ms/step - loss: 0.7304 - accuracy: 0.4997 - val_loss: 0.6961 - val_accuracy: 0.5000
Epoch 2/5
250/250 [==============================] - 106s 425ms/step - loss: 0.7112 - accuracy: 0.5010 - val_loss: 0.6937 - val_accuracy: 0.4994
Epoch 3/5
250/250 [==============================] - 108s 430ms/step - loss: 0.7098 - accuracy: 0.5027 - val_loss: 0.6944 - val_accuracy: 0.4991
Epoch 4/5
250/250 [==============================] - 108s 431ms/step - loss: 0.7147 - accuracy: 0.4934 - val_loss: 0.6932 - val_accuracy: 0.5081
Epoch 5/5
250/250 [==============================] - 108s 431ms/step - loss: 0.7129 - accuracy: 0.4993 - val_loss: 0.6949 - val_accuracy: 0.4969
```

```
[ ] import os
    model_name = 'DogCat.h5'
    save_dir = 'pretrained_model' # pretrained_model # pred_model
    # Save model and weights
    if not os.path.isdir(save_dir):
        os.makedirs(save_dir)
```

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Training using VGG-16

- VGGNet consists of 16 convolutional layers with only 3x3 kernels.
- **Input**: VGG takes in a 224x224 pixel RGB image.
- **Convolutional Layers**: The convolutional layers in VGG use a very small receptive field (3x3, the smallest possible size that still captures left/right and up/down).
- **Fully-Connected Layers**: VGG has three fully-connected layers: 4096 channels each and the last one has 1000 channels
- **Hidden Layers**: All of VGG's hidden layers use ReLU (a huge innovation from AlexNet that cut training time).

Architecture

Results of VGG-16

```
Epoch 1/10
100/100 [==============================] - 33s 333ms/step - loss: 0.6756 - acc: 0.6855 - val_loss: 0.3504 - val_acc: 0.8335
Epoch 2/10
100/100 [==============================] - 33s 332ms/step - loss: 0.4837 - acc: 0.7655 - val_loss: 0.4827 - val_acc: 0.7800
Epoch 3/10
100/100 [==============================] - 33s 328ms/step - loss: 0.4147 - acc: 0.8110 - val_loss: 0.2349 - val_acc: 0.8980
Epoch 4/10
100/100 [==============================] - 33s 330ms/step - loss: 0.4037 - acc: 0.8160 - val_loss: 0.2329 - val_acc: 0.9030
Epoch 5/10
100/100 [==============================] - 33s 327ms/step - loss: 0.4103 - acc: 0.8205 - val_loss: 0.2368 - val_acc: 0.8960
Epoch 6/10
100/100 [==============================] - 33s 326ms/step - loss: 0.3732 - acc: 0.8255 - val_loss: 0.2103 - val_acc: 0.9070
Epoch 7/10
100/100 [==============================] - 33s 332ms/step - loss: 0.3564 - acc: 0.8420 - val_loss: 0.2249 - val_acc: 0.9030
Epoch 8/10
100/100 [==============================] - 33s 329ms/step - loss: 0.3532 - acc: 0.8455 - val_loss: 0.2329 - val_acc: 0.9050
Epoch 9/10
100/100 [==============================] - 33s 329ms/step - loss: 0.3583 - acc: 0.8440 - val_loss: 0.2276 - val_acc: 0.9015
Epoch 10/10
100/100 [==============================] - 33s 331ms/step - loss: 0.3418 - acc: 0.8475 - val_loss: 0.2320 - val_acc: 0.9045
```

Training using GoogleNet

- 22 layers deep.
- The architecture was designed to keep computational efficiency in mind. The idea behind that the architecture can be run on individual devices even with low computational resources.
- Uses many different methods such as 1x1 convolution and global average pooling that enables it to create a deeper architecture.

Architecture

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

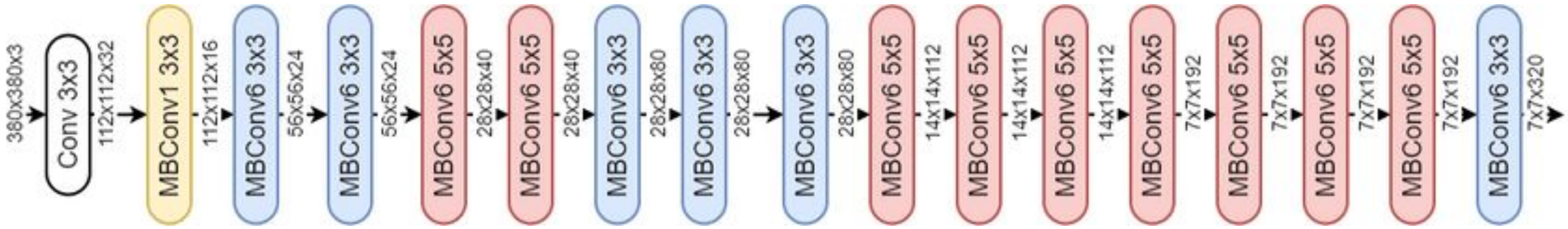
Results of GoogleNet

```
Epoch 1/10
100/100 [==============================] - 28s 278ms/step - loss: 1.1381 - acc: 0.8415 - val_loss: 0.1191 - val_acc: 0.9595
Epoch 2/10
100/100 [==============================] - 26s 256ms/step - loss: 0.4630 - acc: 0.8785 - val_loss: 0.3551 - val_acc: 0.9185
Epoch 3/10
100/100 [==============================] - 27s 267ms/step - loss: 0.3491 - acc: 0.9020 - val_loss: 0.1194 - val_acc: 0.9565
Epoch 4/10
100/100 [==============================] - 26s 256ms/step - loss: 0.3000 - acc: 0.9140 - val_loss: 0.1213 - val_acc: 0.9640
Epoch 5/10
100/100 [==============================] - 26s 265ms/step - loss: 0.3183 - acc: 0.9070 - val_loss: 0.1598 - val_acc: 0.9550
Epoch 6/10
100/100 [==============================] - 26s 256ms/step - loss: 0.3174 - acc: 0.9205 - val_loss: 0.1801 - val_acc: 0.9575
Epoch 7/10
100/100 [==============================] - 27s 266ms/step - loss: 0.3334 - acc: 0.9105 - val_loss: 0.1175 - val_acc: 0.9580
Epoch 8/10
100/100 [==============================] - 26s 257ms/step - loss: 0.3147 - acc: 0.9080 - val_loss: 0.2037 - val_acc: 0.9440
Epoch 9/10
100/100 [==============================] - 26s 263ms/step - loss: 0.2794 - acc: 0.9185 - val_loss: 0.2248 - val_acc: 0.9445
Epoch 10/10
100/100 [==============================] - 26s 256ms/step - loss: 0.3136 - acc: 0.9145 - val_loss: 0.1320 - val_acc: 0.9620
```

EfficientNet

- Alexnet ⟶ VGG-16⟶ Googlenet.
- Process of scaling up CNNs is not well understood; many ways of doing this, mostly arbitrarily chosen.
- Three types of scaling.- width,depth,resolution.
- Efficientnet uses compound scaling.
- Saturation happens if only one type of scaling is done.

EfficientNet



EfficientNet

```
Epoch 1/10
100/100 [==============================] - 32s 324ms/step - loss: 0.3151 - accuracy: 0.9055 - val_loss: 0.0549 - val_accuracy: 0.9670
Epoch 2/10
100/100 [==============================] - 30s 304ms/step - loss: 0.3398 - accuracy: 0.9160 - val_loss: 0.0211 - val_accuracy: 0.9670
Epoch 3/10
100/100 [==============================] - 30s 303ms/step - loss: 0.4132 - accuracy: 0.9070 - val_loss: 0.0252 - val_accuracy: 0.9780
Epoch 4/10
100/100 [==============================] - 30s 303ms/step - loss: 0.3304 - accuracy: 0.9170 - val_loss: 0.5167 - val_accuracy: 0.9810
Epoch 5/10
100/100 [==============================] - 31s 309ms/step - loss: 0.3719 - accuracy: 0.9195 - val_loss: 0.1717 - val_accuracy: 0.9780
Epoch 6/10
100/100 [==============================] - 30s 299ms/step - loss: 0.3617 - accuracy: 0.9145 - val_loss: 3.9468e-06 - val_accuracy: 0.9760
Epoch 7/10
100/100 [==============================] - 31s 307ms/step - loss: 0.3225 - accuracy: 0.9245 - val_loss: 0.0853 - val_accuracy: 0.9710
Epoch 8/10
100/100 [==============================] - 30s 299ms/step - loss: 0.3143 - accuracy: 0.9265 - val_loss: 1.0649e-05 - val_accuracy: 0.9780
Epoch 9/10
100/100 [==============================] - 30s 297ms/step - loss: 0.3283 - accuracy: 0.9225 - val_loss: 0.3379 - val_accuracy: 0.9570
Epoch 10/10
100/100 [==============================] - 30s 298ms/step - loss: 0.3275 - accuracy: 0.9220 - val_loss: 0.4117 - val_accuracy: 0.9790
```

Comparing The Four Models

Name of Model	Number of Layers	Accuracy (%)	Validation Accuracy (%)	Loss (%)	Validation Loss (%)
Alex Net	8	49.93	49.69	71.29	69.49
VGG-16	16	84.75	90.45	34.18	23.2
Efficient Net	17	92.9	97.9	32.75	41.17
Google Net	22	91.45	96.2	31.36	13.2

Plan For Remaining Work

- Working on the MIAS dataset with the basic CNN and then proceeding with other models also.
- Trying to increase the accuracy and lower the losses for the MIAS dataset.

References

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