**Abstract**

Cancer is a group of diseases involving abnormal cell growth

According to American cancer society Cancer continues to be the second most common cause of death in the US, after heart disease. A total of 1.9 million new cancer cases and 609,360 deaths from cancer are expected to occur in the US in 2022, which is about 1,670 deaths a day.

no permanent cure has been developed to combat cancer, early detection is crucial for treatment and survival of patient.

Image recognition and deep learning have been used effectively in detection and treatment of several dangerous diseases, helping in early diagnosis and treatment.

The risk of death from cancer dropped by about 2% a year from 2015 through 2019 compared to 1% a year during the 1990s. Accelerating declines in the cancer death rate show the power of prevention, screening, early diagnosis, treatment.

Deep learning can be used to analyze features allowing detection of breast cancer.

Two of the most common imaging used in breast cancer detection are histopathology and mammography.

\*In our research we aim to compare different deep learning methods on each type of the two imaging, while analyzing the results of the different methods for detection and classification

Key Words: Breast Cancer; Image recognition; Deep Learning; classification

**1. Introduction**

Breast cancer is the second most diagnosed cancer worldwide.[1]

\*(ask ronen if cite is needed or reference is enough)

. Breast cancer occurs in four main types: normal, benign, in-situ carcinoma and invasive carcinoma [2].

In situ carcinoma, the cancer does not effect other organs other than mammary duct lobule system. Benign is not classified as a harmful cancer and involves a minor change in the breast structure. Invasive carcinoma is the deadliest type out of all the four main breast cancer types cause it can spread out to all other organs.

Breast cancer can be diagnosed using one of two approaches: histopathological image analysis or mammography.

Histopathological images are microscopic images of breast tissue that are extremely useful in early treatment of the cancer.

Mammography is specialized medical imaging that uses a low-dose x-ray system to see inside the breasts. A mammography exam, called a mammogram, aids in the early detection and diagnosis of breast diseases in women.

The main difference between:  
mammography is an earlier type of imaging, before breast tissue is collected for histopathology, an x ray image inside the breasts allows us to search for lumps indicating cancer cells, if there is an indication for breast cancer, breast tissue is collected for analysis under microscope for more accurate diagnosis.

We aim to compare and find which type of deep learning methods will satisfy with most accuracy for each type while analyzing the results.

CNN-  
https://www.analyticsvidhya.com/blog/2021/06/breast-cancer-classification-using-deep-learning/

RCNN-  
https://github.com/riblidezso/frcnn\_cad

**SVM**-  
https://towardsdatascience.com/case-study-breast-cancer-classification-svm-2b67d668bbb7

**KNN**-  
<https://www.kaggle.com/code/nsaravana/breast-cancer-using-knn-algorithm/notebook>  
<https://www.codingninjas.com/codestudio/library/breast-cancer-classification-using-knn>  
https://github.com/Manishnir/Breast-Cancer-Prediction-using-KNN

RNN WITH LSTMS  
<https://www.kaggle.com/code/data13/rnn-model-for-breast-cancer-classification/notebook>

These are the methods which will use for our image recognition and classification. We will use each method on mammography and histopathology dataset

We will study each algorithm and make an assumption based on the algorithm aspects on how he will compare against other on each type of images.

The remaining of this paper is structured as follows: Section 2 presents related work which includes surveys conducted in breast cancer area. Section 3 explains the methodology used to conduct this research. Section 4 presents the obtained results and related discussions. Lastly, Section 5 concludes the paper and suggests future research directions.

References:

1 S. Germano and L. O'Driscoll, Curr. Cancer Drug Targets, 2009, 9, 398–418.

**2 Background and Related Work**

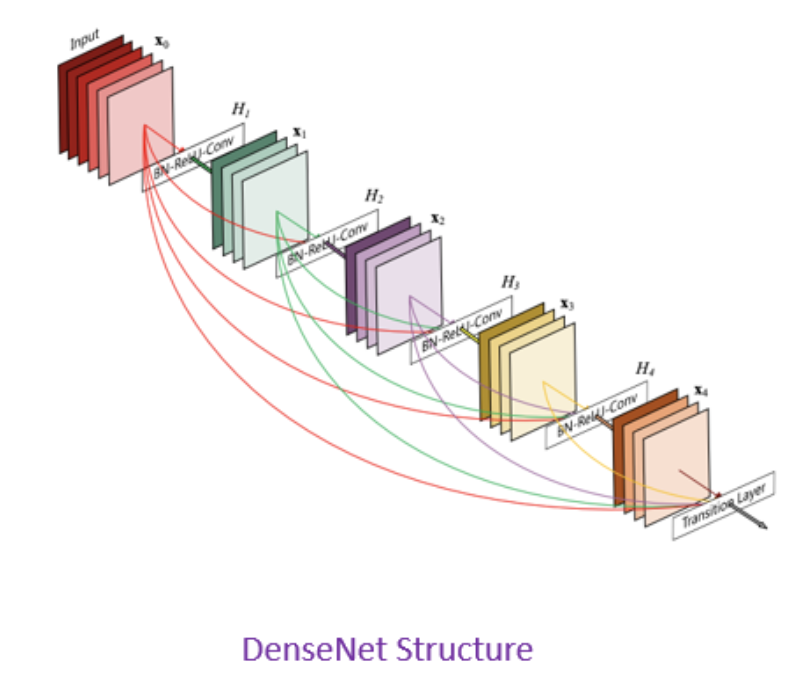
**2.1 Background – DenseNet-121 (Densely Connected Convolutional Networks)**

In a traditional feed-forward Convolutional Neural Network (CNN), each convolutional layer except the first one (which takes in the input), receives the output of the previous convolutional layer and produces an output feature map that is then passed on to the next convolutional layer. Therefore, for 'L' layers, there are 'L' direct connections, one between each layer and the next layer.

However, as the number of layers in the CNN increase, i.e., as they get deeper, the '**vanishing gradient**' problem arises. This means that as the path for information from the input to the output layers increases, it can cause certain information to 'vanish' or get lost which reduces the ability of the network to train effectively.

**2.1.1 Vanishing Gradient problem solve**

DenseNets resolve vanishing gradient problem by modifying the standard CNN architecture and simplifying the connectivity pattern between layers. In a DenseNet architecture, each layer is connected directly with every other layer, hence the name Densely Connected Convolutional Network. For 'L' layers, there are L(L+1)/2 direct connections.



**2.1.2 DenseNet Components**

DenseNet components including 4 parts:

* Connectivity
* DenseBlocks
* Growth Rate
* Bottleneck layers

**2.1.2.1 Connectivity**

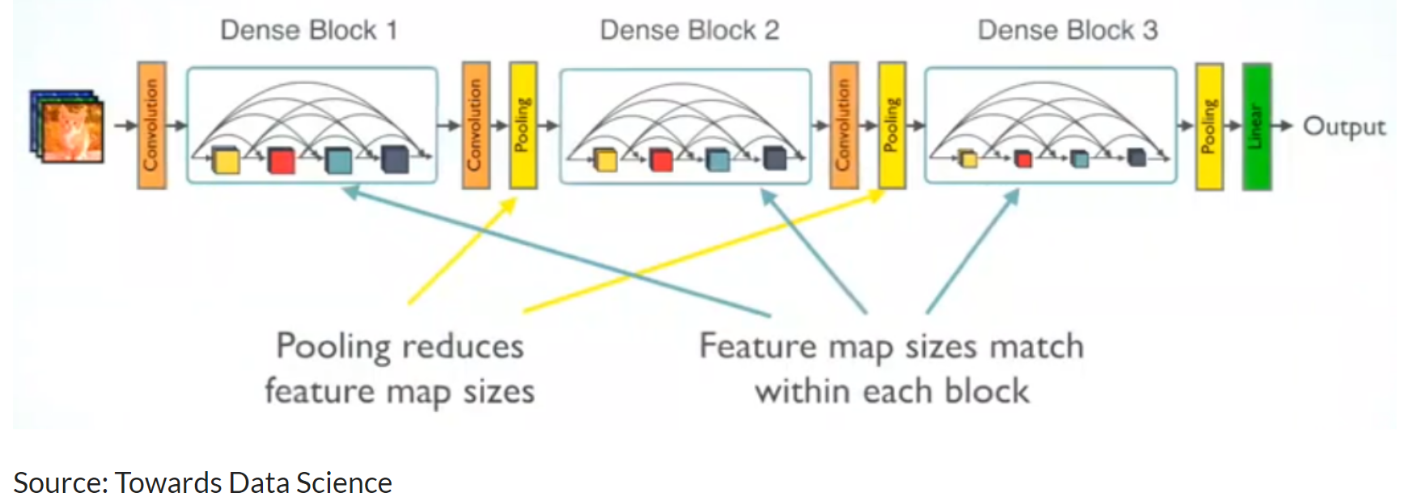
in each layer, the feature maps of all the previous layers are not summed, but concatenated and used as inputs. Consequently, DenseNets require fewer parameters than an equivalent traditional CNN, and this allows for feature reuse as redundant feature maps are discarded. So, the lth layer receives the feature-maps of all preceding layers, x0,...,xl-1, as input:

**2.1.2.2 DenseBlocks**

The use of the concatenation operation is not feasible when the size of feature maps changes. However, an essential part of CNNs is the down-sampling of layers which reduces the size of feature-maps through dimensionality reduction to gain higher computation speeds.

To enable this, DenseNets are divided into DenseBlocks, where the dimensions of the feature maps remains constant within a block, but the number of filters between them is changed. The layers between the blocks are called Transition Layers which reduce the the number of channels to half of that of the existing channels.

For each layer, from the equation above, Hl is defined as a composite function which applies three consecutive operations: batch normalization (BN), a rectified linear unit (ReLU) and a convolution (Conv).



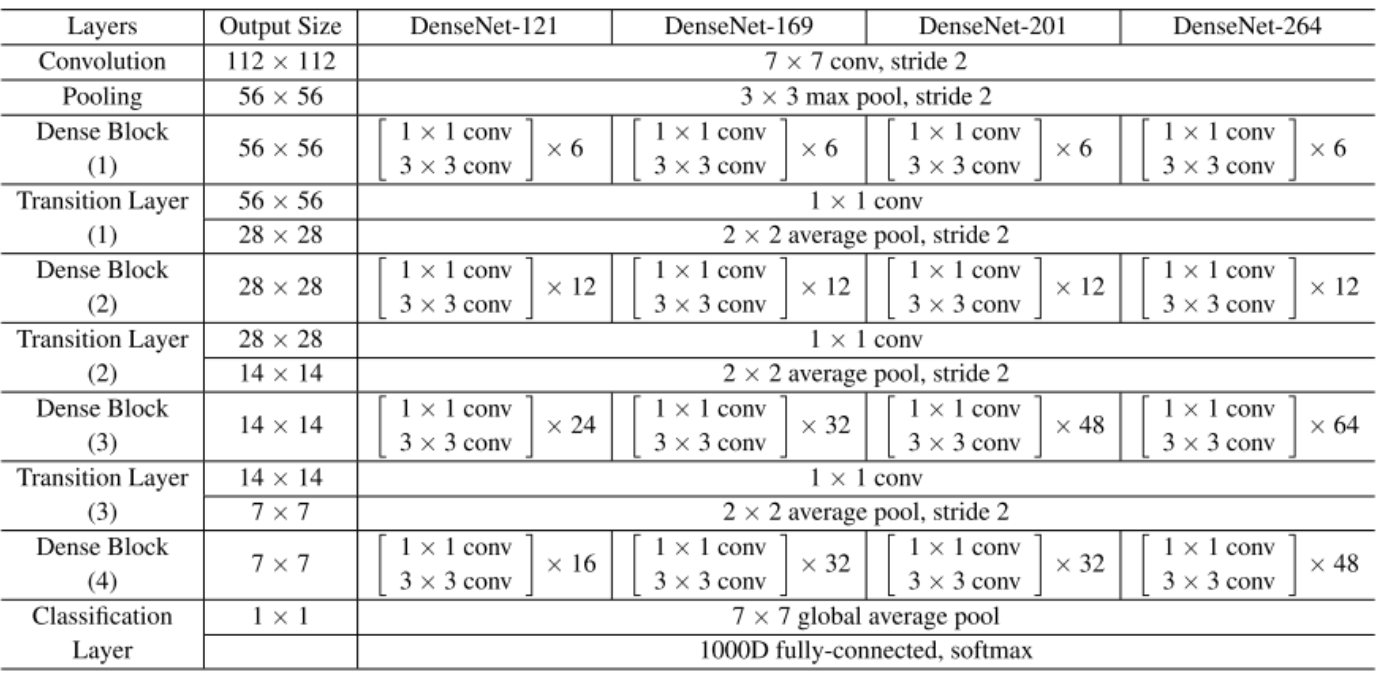
In the above image, a deep DenseNet with three dense blocks is shown. The layers between two adjacent blocks are the transition layers which perform downsampling (i.e. change the size of the feature-maps) via convolution and pooling operations, whilst within the dense block the size of the feature maps is the same to enable feature concatenation.

**2.1.2.3 Growth Rate**

One can think of the features as a global state of the network. The size of the feature map grows after a pass through each dense layer with each layer adding 'K' features on top of the global state (existing features). This parameter 'K' is referred to as the growth rate of the network, which regulates the amount of information added in each layer of the network. If each function H l produces k feature maps, then the lth layer has

**2.1.2.4 Bottleneck layers**

Although each layer only produces k output feature-maps, the number of inputs can be quite high, especially for further layers. Thus, a 1x1 convolution layer can be introduced as a bottleneck layer before each 3x3 convolution to improve the efficiency and speed of computations.

**2.1.3 DenseNet Architecture**

A summarization of the various architectures implemented for the ImageNet database have been provided in the table above. Stride is the number of pixels shifts over the input matrix. A stride of 'n' (default value being 1), indicates that the filters are moved 'n' pixels at a time.

Using the DenseNet-121 architecture to understand the table, we can see that every dense block has varying number of layers (repetitions) featuring two convolutions each; a 1x1 sized kernel as the bottleneck layer and 3x3 kernel to perform the convolution operation.

Also, each transition layer has a 1x1 convolutional layer and a 2x2 average pooling layer with a stride of 2. Thus, the layers present are as follows:

1. Basic convolution layer with 64 filters of size 7X7 and a stride of 2.
2. Basic pooling layer with 3x3 max pooling and a stride of 2.
3. Dense Block 1 with 2 convolutions repeated 6 times.
4. Transition layer 1 (1 Conv + 1 AvgPool).
5. Dense Block 2 with 2 convolutions repeated 12 times.
6. Transition layer 2 (1 Conv + 1 AvgPool).
7. Dense Block 3 with 2 convolutions repeated 24 times.
8. Transition layer 3 (1 Conv + 1 AvgPool).
9. Dense Block 4 with 2 convolutions repeated 16 times.
10. Global Average Pooling layer- accepts all the feature maps of the network to perform classification.
11. Output layer.

Therefore, DenseNet-121 has the following layers:

* 1 7x7 Convolution
* 58 3x3 Convolution
* 61 1x1 Convolution
* 4 AvgPool
* 1 Fully Connected Layer

To summarize DenseNet-121 has 120 Convolutions and 4 AvgPool.

All layers i.e., those within the same dense block and transition layers, spread their weights over multiple inputs which allows deeper layers to use features extracted early on.

**2.1.4 Advantages of the DenseNet**

Two of the most obvious Advantages of the DenseNet are

**Parameter efficiency** and **Implicit deep supervision** which result in more compact models and have achieved state of the art of performances and better results across competitive datasets, as compared to their standard CNN counterpart.

* **Parameter efficiency** – Every layer adds only a limited number of parameters- for e.g. only about 12 kernels are learned per layer
* **Implicit deep supervision** – Improved flow of gradient through the network- Feature maps in all layers have direct access to the loss function and its gradient.