# Skin Cancer Segmentation

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# Outline

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# Introduction
## Skin Cancer

- Melanoma - the most dangerous form of skin cancer
- The rates of melanoma have been rising for the last 30 years
- Every year, about **5.4 million new cases** of skin cancer are diagnosed in the United States
- Early detection is the key to proper treatment of skin cancer
  - early-stage: **97%** five-year survival rate
  - final-stage: **14%** five-year survival rate

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- The International Skin Imaging Collaboration (ISIC) is an international effort to improve melanoma diagnosis
- The goal of the challenge is to help participants develop image analysis tools to **enable the automated diagnosis of melanoma** from dermoscopic images
- Lesion Segmentation challenge provides training data ($\sim$2000 images) with size of $3000 \times 2000$ pixels

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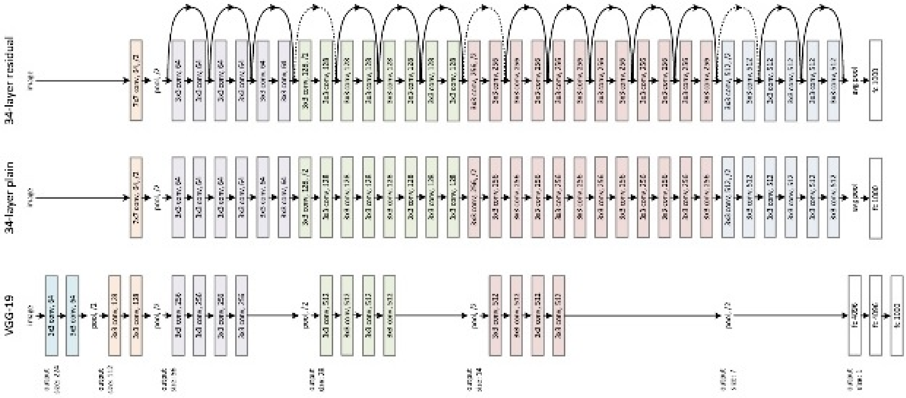
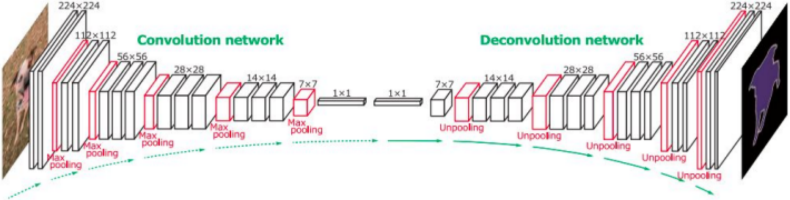
**Pattern analysis outperforms the rest!!!**

# Approaches
## Deep Residual Networks



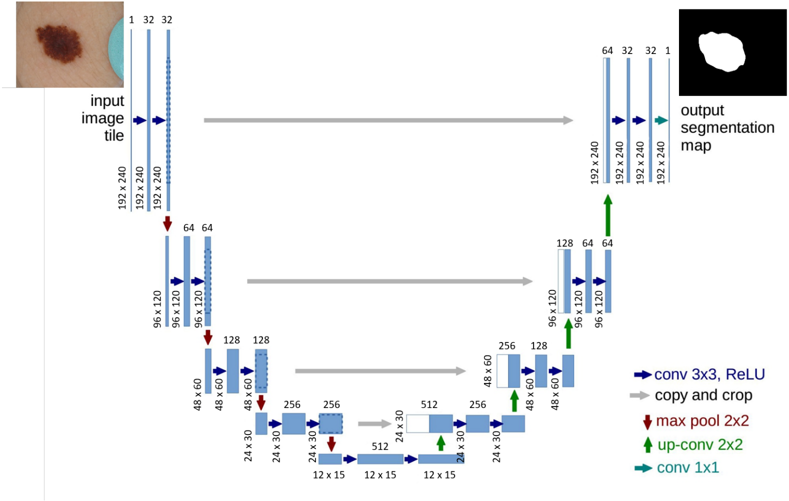
# Approaches

## Convolutional-Deconvolutional Neural Networks



# Our approach

## Modified U-Net



- Python and Matlab
- **Deeplearning4j** deep dearning for Java
- **Caffee** developed by Berkeley AI Research
- **TensorFlow** developed by Google
- **Keras** deep learning API with TensorFlow in the back end

# Approaches

## Frameworks and Programming languages

- Python and Matlab
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# Our Approach

## Pre-processing

- Image vectorization
- Mean subtraction and normalization

$$X = \frac{x - \mu}{\sigma} \quad (1)$$

where $x$ is input image, $\mu$ is mean of pixel values, $\sigma$ is standard deviation of pixels in the image, and $X$ is normalized image.

- Image resizing $192 \times 240$

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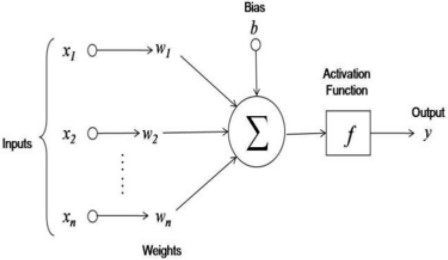
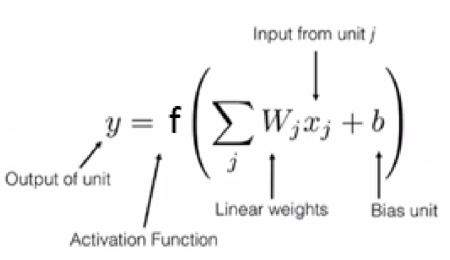
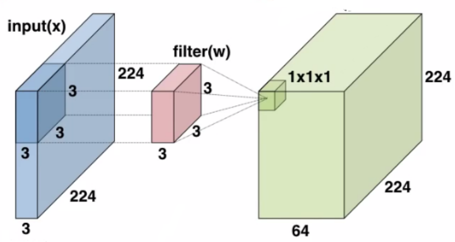
# Our Approach
## Mathematical Model of Neuron

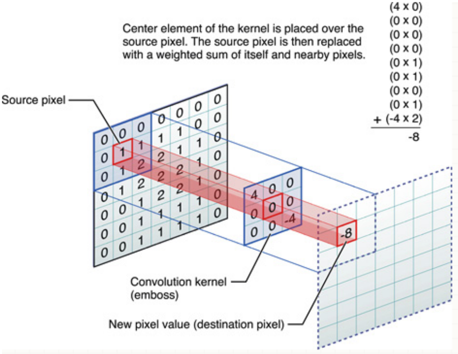


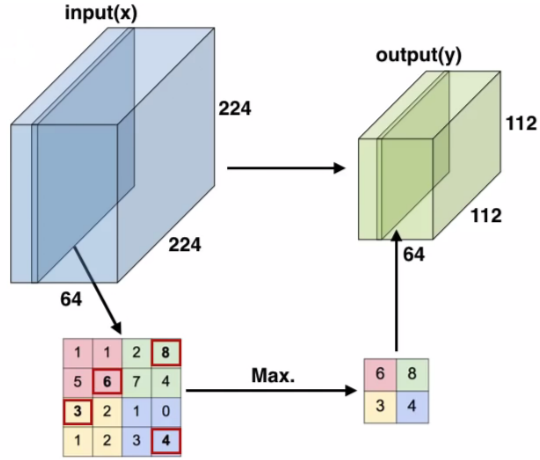
# Our Approach

## Convolutional Layer

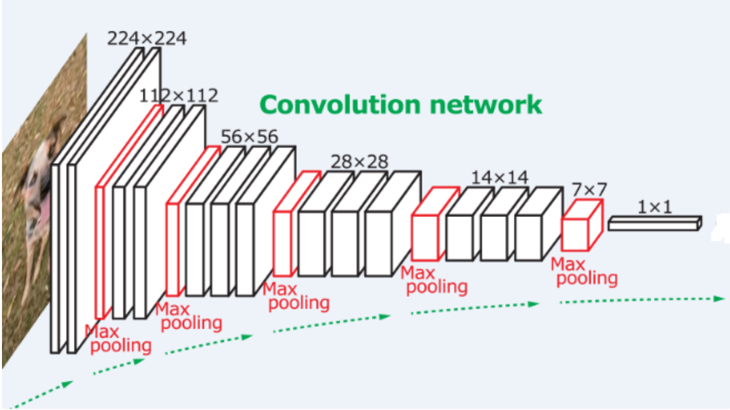


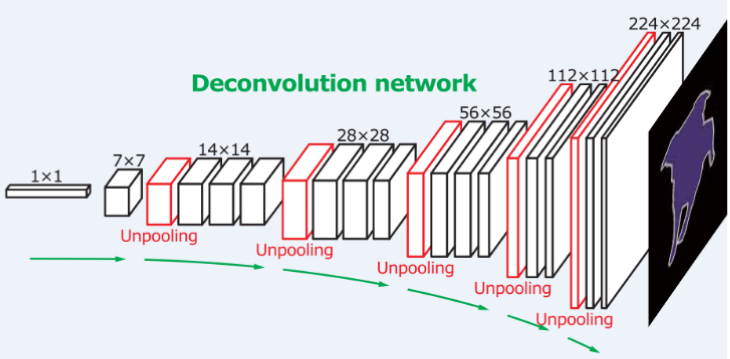
# Our Approach
## Max Pooling Layer

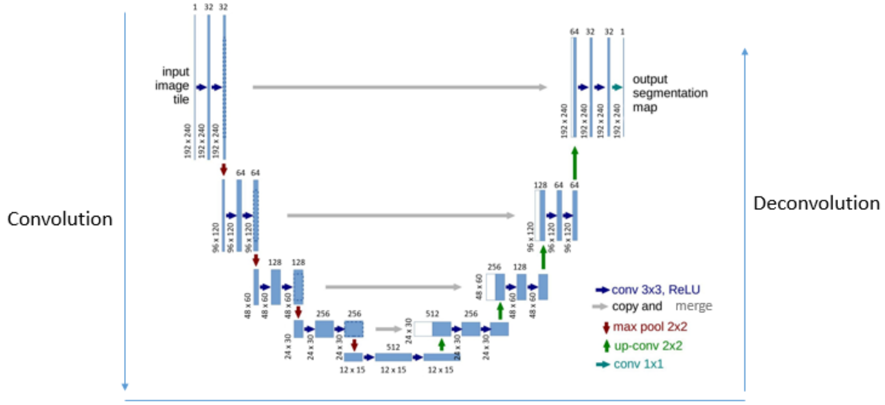


# Our Approach
## Convolutional Neural Network



# Our Approach
## Deconvolutional Neural Network





Convolution
Deconvolution
input image tile
output segmentation map
conv 3x3, ReLU
copy and merge
max pool 2x2
up-conv 2x2
conv 1x1
1 32 32
192 x 240
64 64
96 x 120
128 128
48 x 60
256 256
24 x 30
512
12 x 15
64 32 32 1
128 64 64

# Our Approach

## Training

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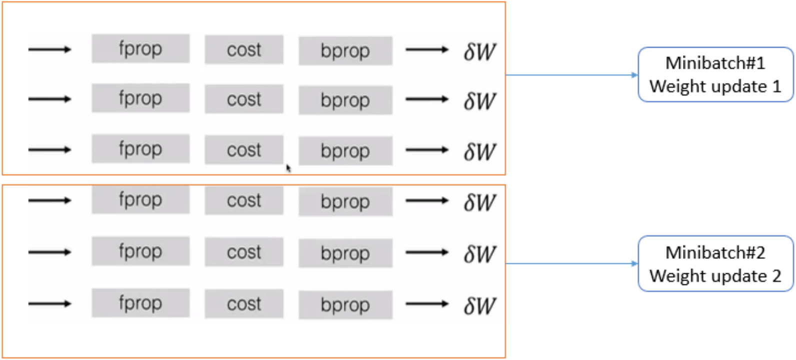
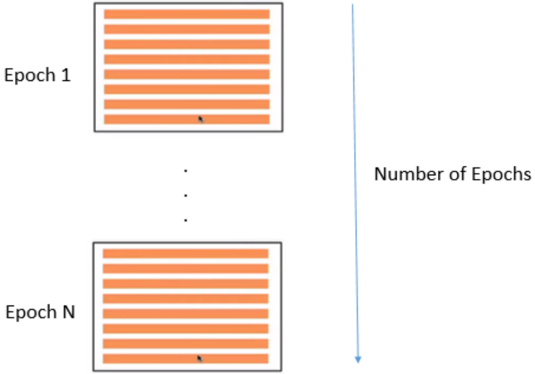
## Training Mini Batch Size

- Number of training images in one forward and backward pass
- Mini batch-size = 10



# Our Approach
## Training Epoch

- How many times every image has been seen during training?
- Shuffling



# Our Approach
## Training Parameters

- **Learning rate**
  - Step size for which the weights of model are updated
  - $10^{-5}$
- **Loss function** (also called cost function)
  - Evaluate the penalty between the prediction and the ground truth label in every batch
  - Dice Coefficient is used as loss function
- **Optimizer**
  - Optimal set of hyper parameters for the model
  - Adam optimization algorithms

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# Our Approach
## Testing

- Test image
- Launch the trained model

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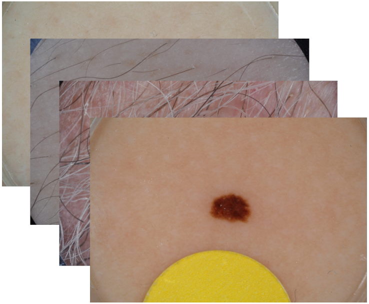
# Result and Discussion

## Test Bench

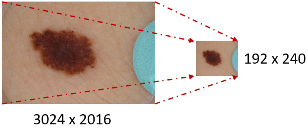
- Dell Inspirion 15 with 4 GB NVIDIA GEFORCE 960M GPU
- University of Cassino Computer with 12 GB NVIDIA TITAN X GPU
- 450 epochs take **81 hours of training**

150 Test sets of three classes:

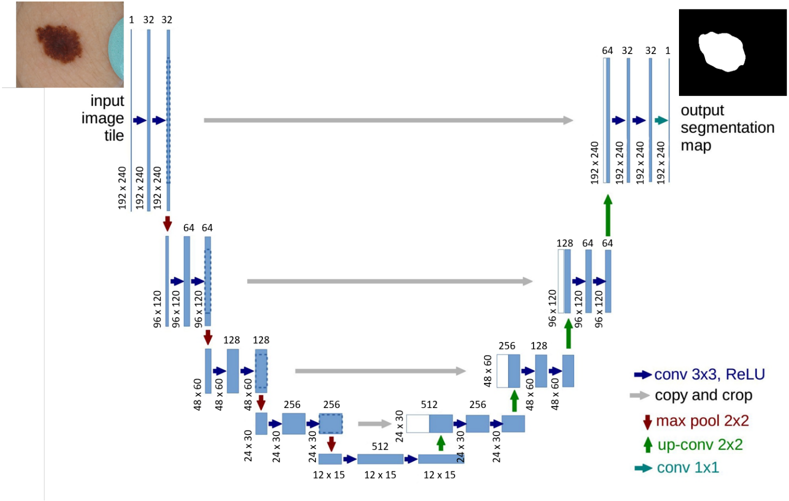
- 30 Melanoma – malignant skin tumor
- 78 Nevus – benign skin tumor (melanocytic)
- 42 Seborrheic keratosis – benign skin tumor



1. Images are resized to 192 x 240 pixels
2. Then images are vectorized and stored in numpy array file

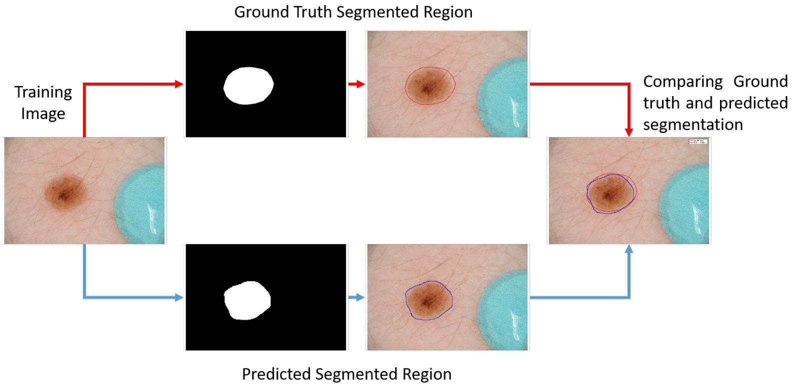


# Result and Discussion
## Test Data



# Result and Discussion

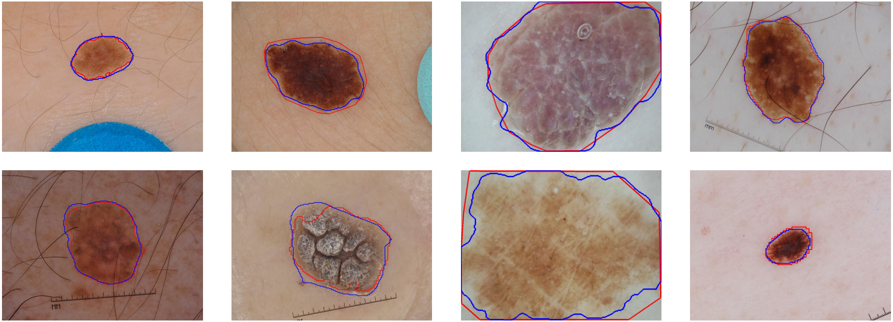
## Flowchart



# Result and Discussion

## Predicted segmentation & Ground truth mask on some of the test images

The red mask denotes the ground truth while the blue mask denotes the predicted mask from the convolutional neural network.

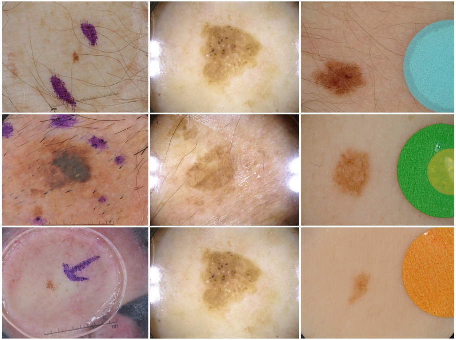


# Result and Discussion

## Problems of Dataset of Skin Lesion Segmentation Challenge on ISBI 2017

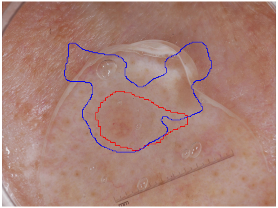
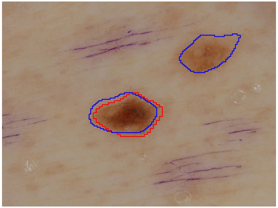
From the training set, many of the training images had artifacts

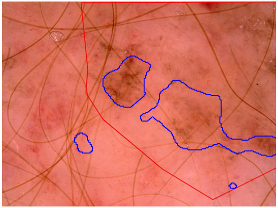
- Images with markings
- Images with bright lights at the edge
- images with color patches

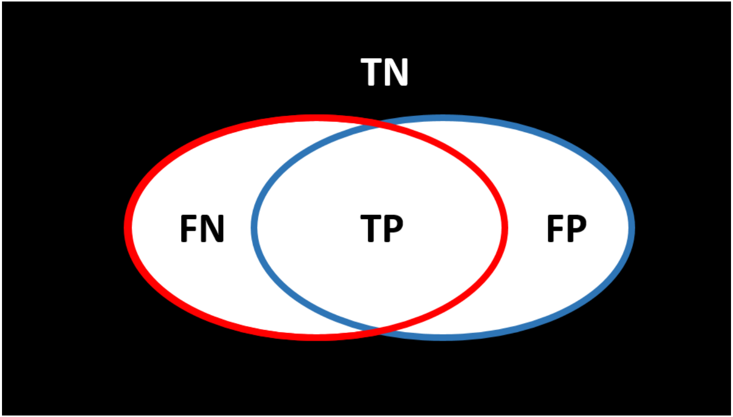


# Result and Discussion

## Some of the poorly segmented results from the testing set



TN
FN
TP
FP

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{FN}+\text{TN}}$$

$$\text{Jaccard Index} = \frac{\text{TP}}{\text{TP}+\text{FN}+\text{FP}}$$

$$\text{Dice Coefficient} = \frac{2 \times \text{TP}}{2 \times \text{TP}+\text{FN}+\text{FP}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}}$$

Table: Comparison of the results

| Methods | Accuracy | Dice Coefficient | Jaccard Index | Sensitivity | Specificity |
|---|---|---|---|---|---|
| **Our Approach** | **0.9403** | **0.8053** | **0.7116** | **0.8531** | **0.9308** |
| Yading Yuan | 0.9340 | 0.8490 | 0.7650 | 0.8250 | 0.9750 |
| Matt Berseth | 0.9320 | 0.8470 | 0.7620 | 0.8200 | 0.9780 |
| Lei Bi | 0.9340 | 0.8440 | 0.7600 | 0.8020 | 0.9850 |
| Euijoon Ahn | 0.9340 | 0.8420 | 0.7580 | 0.8010 | 0.9840 |
| Recod Titans | 0.9310 | 0.8390 | 0.7540 | 0.8170 | 0.9700 |
| Jeremy Kawahara | 0.9300 | 0.8370 | 0.7520 | 0.8130 | 0.9760 |
| Jahanifar Zamani | 0.9300 | 0.8390 | 0.7490 | 0.8100 | 0.9810 |
| INESC TECHNALIA | 0.9220 | 0.8240 | 0.7350 | 0.8130 | 0.9680 |
| Vic Lee | 0.9220 | 0.8100 | 0.7180 | 0.7890 | 0.9750 |
| Juana M.Guitierrez | 0.9150 | 0.7970 | 0.7150 | 0.7740 | 0.9700 |

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# Conclusion

## Problems Faced

Problems faced during the implementation of the CNN on Skin Cancer segmentation

- Time constraint: Training the dataset even without data augmentation takes a lot of time
- Dataset limited: Limited training set, most of the images has background artifact

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Although, we were still able to get better percentage of accuracy compared to the other methods used on the same dataset, further improvements are still possible to yield even a better result:

- **Data Augmentation:** The limited data can be augmented using translation, rotation, flipping and elastic distortion
- **Cropping:** Cropping can be performed on the training set images with unnecessary objects, i.e unwanted hair, color patch, markings, bright spots etc.

# Q & A

Thank you for listening