Brain Tumor Detection and Localization using Deep Learning

Title : “Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm”
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https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation

SUBJECT: APPLIED MACHINE LEARNING (ITCS 5156)

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Problem & Challenges

- RECENT ANALYSIS IDENTIFIED DISTINCT GENOMIC SUBTYPES OF LOWER-GRADE GLIOMA TUMORS WHICH ARE ASSOCIATED WITH SHAPE FEATURES. IN THIS STUDY, WE EXPLORE A FULLY AUTOMATIC WAY TO QUANTIFY TUMOR IMAGING CHARACTERISTICS USING DEEP LEARNING-BASED SEGMENTATION AND TEST WHETHER THESE CHARACTERISTICS ARE PREDICTIVE OF TUMOR GENOMIC SUBTYPES.

- WE WILL USE RESUNET ARCHITECTURE TO SOLVE THE CURRENT TASK.

Continued…

- THE PRIMARY CHALLENGES WITH ORIGINAL APPROACH OF USING CNNS IS THE VANISHING GRADIENT WITH INCREASING DEPTH.
- RESIDUAL NEURAL NETWORK INCLUDES “SKIP CONNECTION” FEATURE WHICH ENABLES TRAINING OF LAYERS WITHOUT VANISHING GRADIENT ISSUES. RESNET WORKS BY ADDING “IDENTITY MAPPINGS” ON TOP OF THE CNN.

Motivation

TO EXPLORE HOW DEEP LEARNING METHODOLOGIES CAN HELP IN THE HEALTH INDUSTRY PRIMARILY FOR CANCER/TUMOR DETECTION AND LOCALIZATION AND IMPLEMENT THEM ON AVAILABLE DATASET TO LEARN HOW THE PROCEDURE WORKS AND HOW IMPACTFUL IT IS.

Existing/Previous related approaches

- THE FIRST CNN LAYERS ARE USED TO EXTRACT HIGH LEVEL GENERAL FEATURES. THE LAST COUPLE OF LAYERS ARE USED TO PERFORM CLASSIFICATION (ON A SPECIFIC TASK).
- LOCAL RESPECTIVE FIELDS SCAN THE IMAGE FIRST SEARCHING FOR SIMPLE SHAPES SUCH AS EDGES/LINES. THESE EDGES ARE THEN PICKED UP BY THE SUBSEQUENT LAYER TO FORM MORE COMPLEX FEATURES.
- CNN IS LARGELY USED WHEN THE WHOLE IMAGE IS NEEDED TO BE CLASSIFIED AS A CLASS LABEL. BUT MANY TASKS REQUIRES TO CLASSIFY EACH PIXEL OF THE IMAGE.
- AS CNNS GROW DEEPER, VANISHING GRADIENT TEND TO OCCUR WHICH NEGATIVELY IMPACT NETWORK PERFORMANCE.

The Method (that I duplicated)

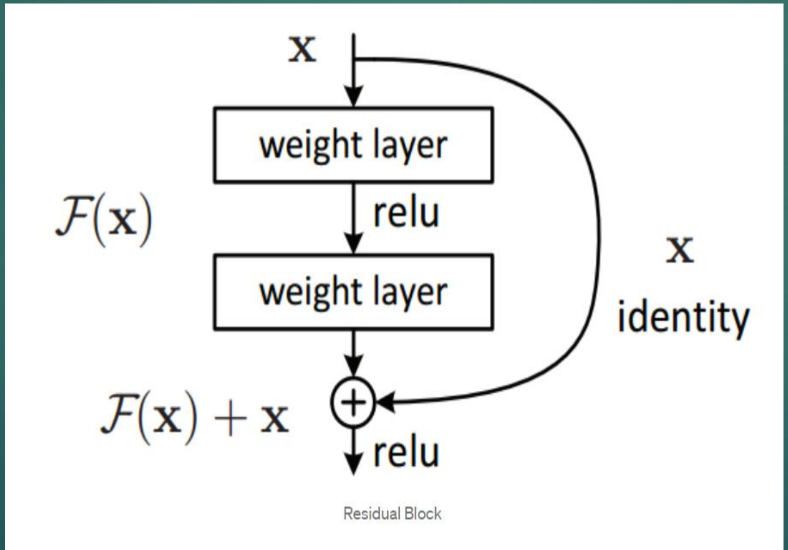
- THE METHOD USES DEEP LEARNING STRATEGIES BASED ON CNN FOR TUMOR DETECTION AND LOCALIZATION. WE USE THE CNN-BASED RESUNET MODEL TO IDENTIFY THE TUMORS.

- MORE LAYERS IN CLASSIC NEURAL NETWORKS IMPLY A BETTER NETWORK, BUT DUE TO THE VANISHING GRADIENT PROBLEM, THE FIRST LAYER'S WEIGHTS WILL NOT BE UPDATED APPROPRIATELY BY BACK-PROPAGATION. THE ERROR GRADIENT IS MODEST BECAUSE IT IS BACK-PROPAGATED TO PRIOR LAYERS BY REPEATED MULTIPLICATION.

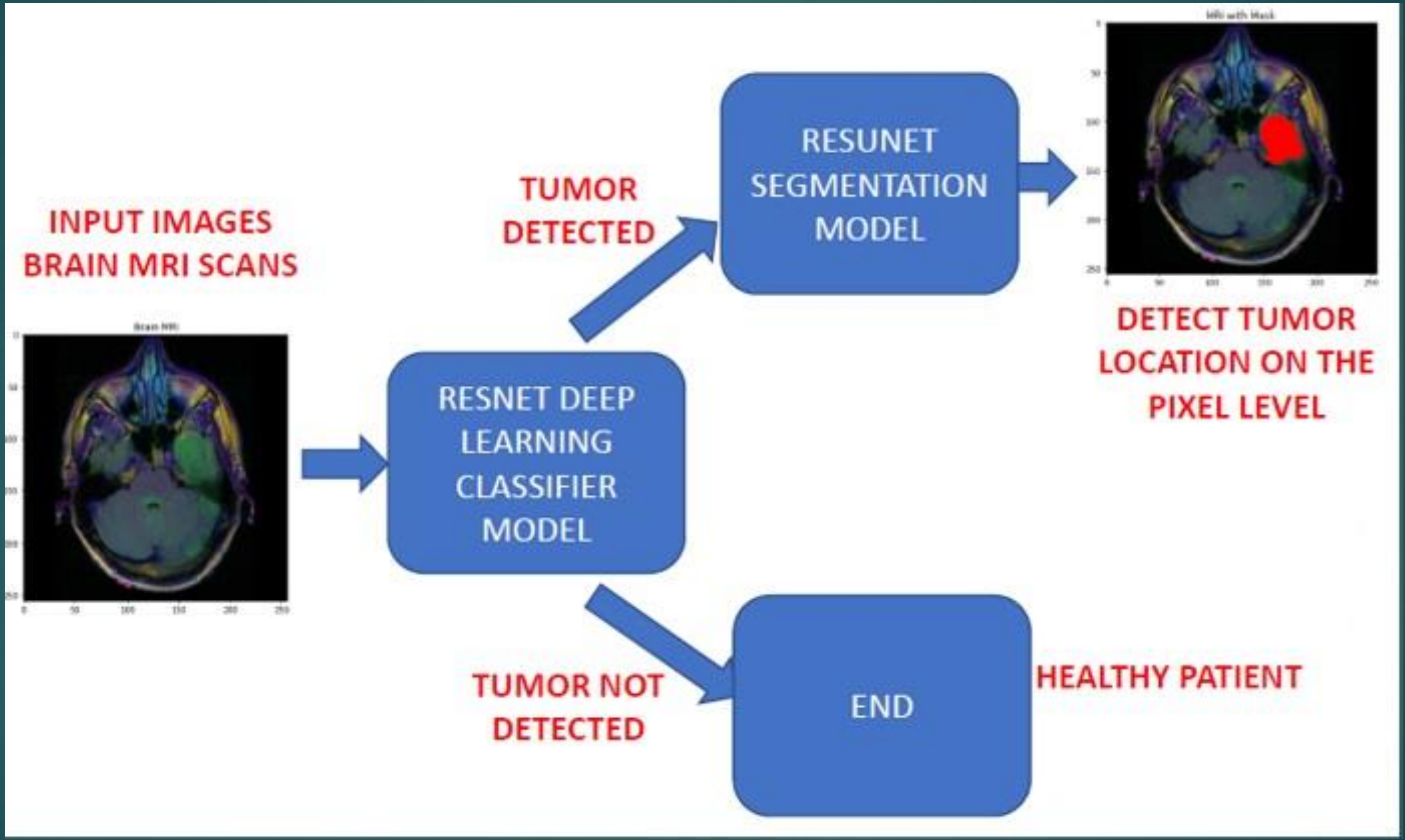
- AS A RESULT, AS THE NETWORK GROWS IN LAYERS, ITS PERFORMANCE BECOMES SATURATED AND BEGINS TO DECLINE SIGNIFICANTLY. THE IDENTITY MATRIX IS USED BY RES-NET TO TACKLE THIS PROBLEM. WHEN USING THE IDENTITY FUNCTION FOR BACK-PROPAGATION, THE GRADIENT IS ONLY MULTIPLIED BY ONE. THIS ENSURES THAT THE INPUT IS PRESERVED AND THAT NO DATA IS LOST.

Continued…….

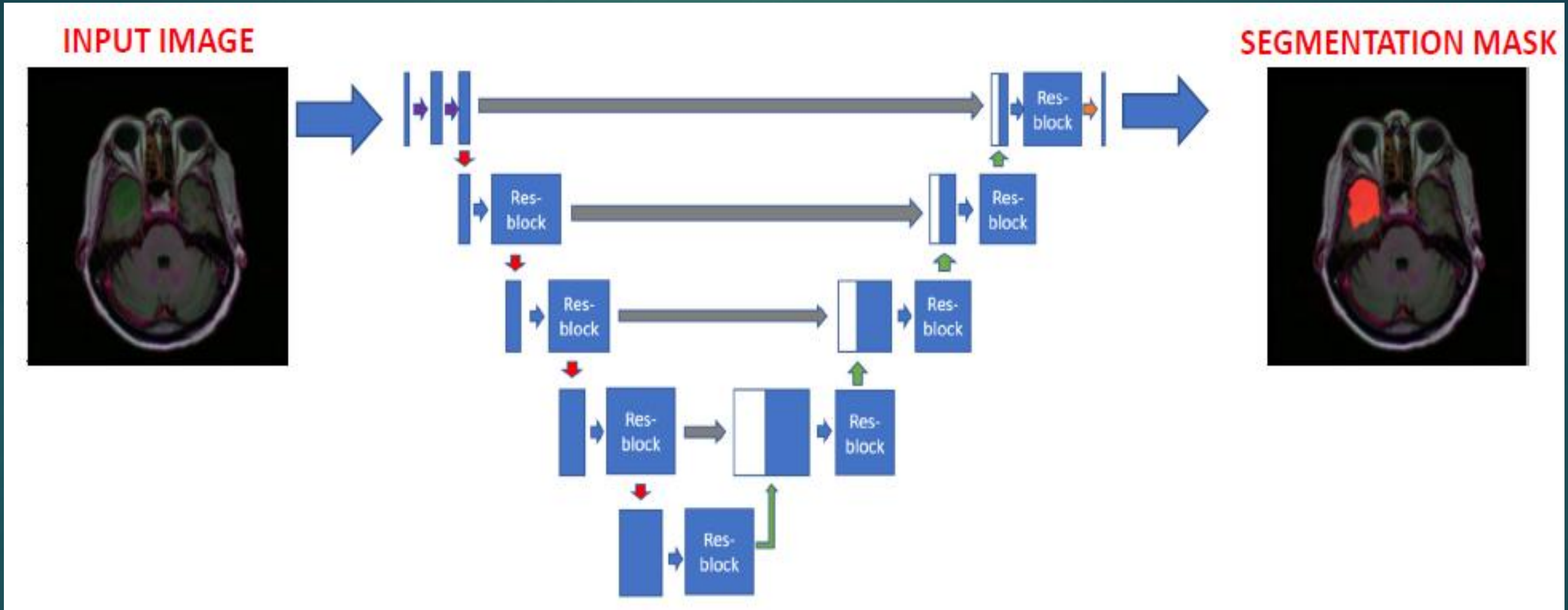
- RESNET EMPLOYS A SKIP CONNECTION, WHICH MEANS THAT AN ORIGINAL INPUT IS ALSO APPENDED TO THE CONVOLUTION BLOCK'S OUTPUT. THIS AIDS IN THE RESOLUTION OF THE VANISHING GRADIENT PROBLEM BY PROVIDING AN ALTERNATE PATH FOR THE GRADIENT TO FLOW THROUGH. THEY ALSO EMPLOY THE IDENTITY FUNCTION, WHICH AIDS THE HIGHER LAYER IN PERFORMING AS WELL AS THE LOWER LAYER, IF NOT BETTER.
- IN A NETWORK WITH RESIDUAL BLOCKS, EACH LAYER FEEDS INTO THE NEXT LAYER AND DIRECTLY INTO THE LAYERS ABOUT SOME HOPS AWAY.



Basic Layout



- RESUNET ARCHITECTURE COMBINES UNET BACKBONE ARCHITECTURE WITH RESIDUAL BLOCKS TO OVERCOME THE VANISHING GRADIENTS PROBLEMS PRESENT IN DEEP ARCHITECTURES.
- UNET ARCHITECTURE IS BASED ON FULLY CONVOLUTIONAL NETWORKS AND MODIFIED IN A WAY THAT IT PERFORMS WELL ON SEGMENTATION TASKS.
- RESUNET CONSISTS OF THREE PARTS:
  1. ENCODER OR CONTRACTING PATH
  2. BOTTLENECK
  3. DECODER OR EXPANSIVE PATH


INPUT IMAGE
SEGMENTATION MASK
Res-block
Res-block
Res-block
Res-block
Res-block
Res-block
Res-block
Res-block
Res-block

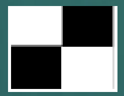
Masking

- THE GOAL OF IMAGE SEGMENTATION IS TO UNDERSTAND THE IMAGE AT THE PIXEL LEVEL. IT ASSOCIATES EACH PIXEL WITH A CERTAIN CLASS. THE OUTPUT PRODUCE BY IMAGE SEGMENTATION MODEL IS CALLED A "MASK" OF THE IMAGE.
- MASKS CAN BE REPRESENTED BY ASSOCIATING PIXEL VALUES WITH THEIR COORDINATES. FOR EXAMPLE IF WE HAVE A BLACK IMAGE OF SHAPE (2,2), THIS CAN BE REPRESENTED AS:

    [[0, 0],
    [0, 0]]

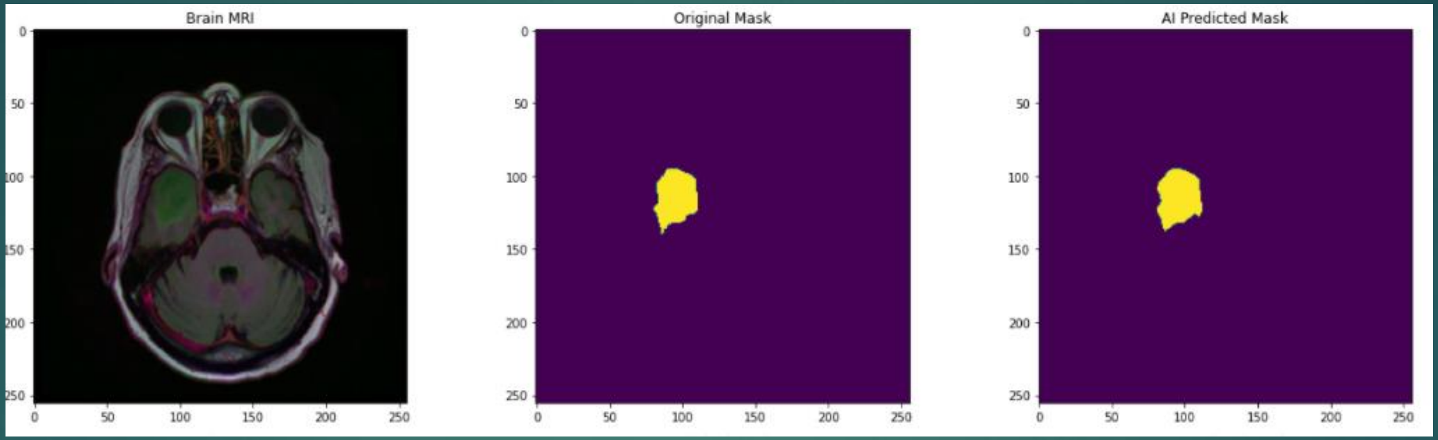
- IF OUR OUTPUT MASK IS AS FOLLOWS:

    [[255, 0],
    [0,255]]

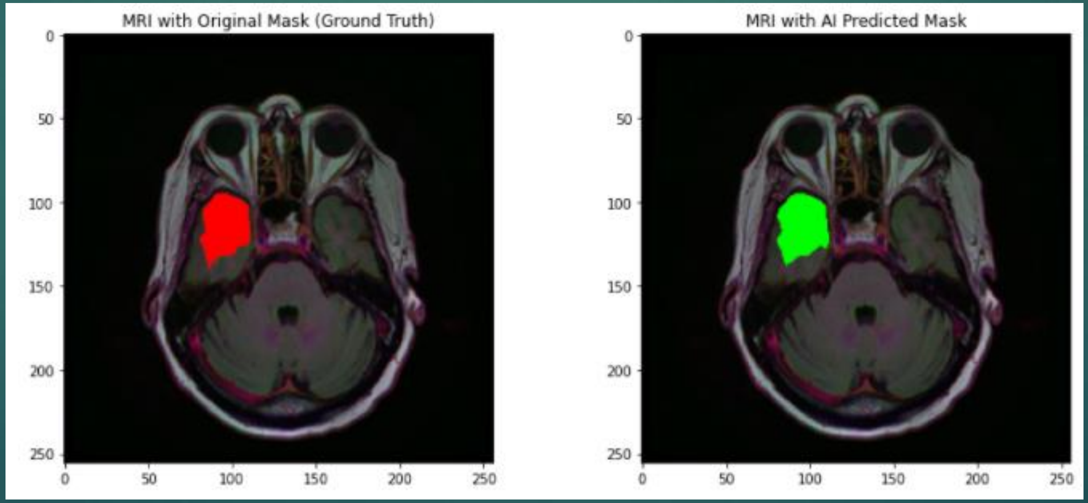


- TO REPRESENT THIS MASK WE HAVE TO FIRST FLATTEN THE IMAGE INTO A 1-D ARRAY. THIS WOULD RESULT IN SOMETHING LIKE [255,0,0,255] FOR MASK. THEN, WE CAN USE THE INDEX TO CREATE THE MASK. FINALLY WE WOULD HAVE SOMETHING LIKE [1,0,0,1] AS OUR MASK.

Results



Brain MRI
Original Mask
AI Predicted Mask



MRI with Original Mask (Ground Truth)
MRI with AI Predicted Mask

Observations

- THE ACCURACY OF THE MODEL IS AROUND 90%.

- I AM USING A USING CUSTOM LOSS FUNCTION TO TRAIN THIS RESUNET NAMELY 'FOCAL TVERSKY ATTENTION U-NET' FOR ITS STABILITY WITH RESUNET ARCHITECTURE.

  HTTPS://GITHUB.COM/NABSABRAHAM/FOCAL-TVERSKY-UNET

- The project is almost complete with minor changes and some assessments/finetuning remaining.

Conclusion and future work

- ResUnet Architecture is considerably accurate for the task of tumor segmentation.
- In the future works, I would like to perform further finetuning of the model to see how efficient it would be to localize tumors in other areas of the body.