Dense Gated Blocks

Towards layers relationships in densely connected blocks

Joseph Wagane FAYE
Univ. Rennes, INSA Rennes, IETR - UMR CNRS 6164

VAADER “AI for Image” Reading Group – 2021-18-03

Outlines

- Speaker presentation
- DenseNet Reminder
- Dense Gated Blocks
- Application for Brain Lesion Segmentation
- Conclusion

Speaker Presentation

- **Joseph Wagane FAYE**

- INSA Rennes Engineer« Electronique - CDTI», 2019 (Before that, I was student at SRC departement 2016-2017)

    - R&D apprentice engineer at Orange Labs Lannion:
        - Study of the problem of classifying acoustic signals in real conditions using machine learning techniques.
        - Design of an algorithm for sound recognition related to the home environment and prototyping of a dedicated tool.
        - Demonstration at the Orange 2019 research fair.

- Research Engineer since December 2019 for RAISE project:
    - Deep learning field : Monocular depth estimation based on CNN and their efficient evaluation.

- Hobbies
    - Football, Soccer, Combat sports
    - Chess
    - Politics, History and Civilization

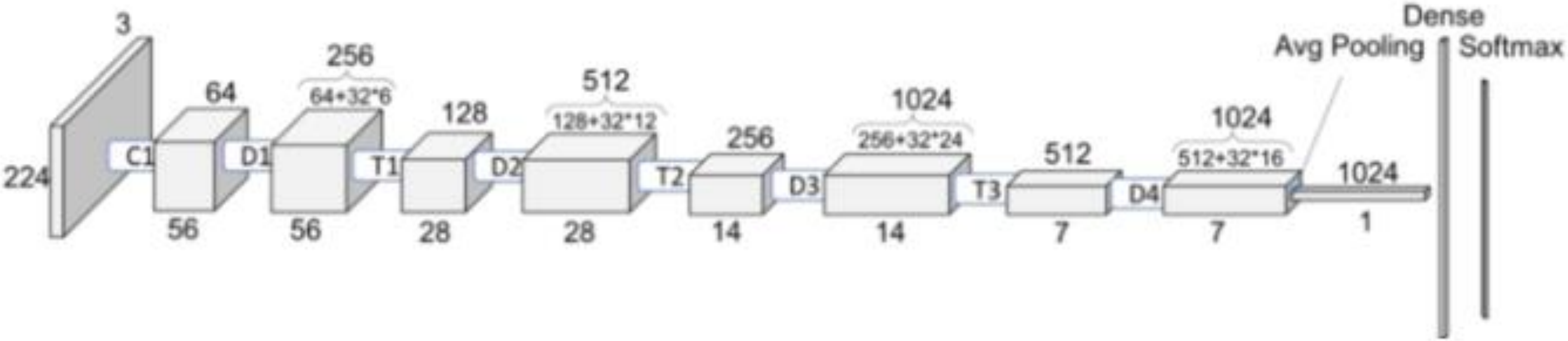
The Paper

A Dense-Gated U-Net for Brain Lesion Segmentation

Zhongyi Ji[1], Xiao Han[1], Tong Lin[*2], and Wenmin Wang[3]
[1]School of Electronic and Computer Engineering, Peking University Shenzhen Graduate School
[2]The Key Laboratory of Machine Perception (MOE), School of EECS, Peking University; and Peng Cheng Laboratory
[3]International Institute of Next Generation Internet, Macau University of Science and Technology
jizhongyi@pku.edu.cn, hanxiao18@pku.edu.cn, lintong@pku.edu.cn, wmwang@must.edu.mo

- This is a paper in **2020 VCIP**
- In this paper :
  - A **Dense-Gated Unet (DGNet)**, whicj is a hybrid of Dense-gated blocks and U-Net is proposed
  - **DGNet** can achieve weighted concatenation and suppress useless features.

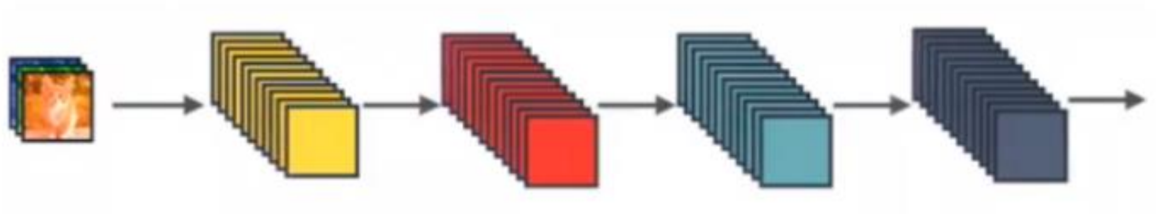
DenseNet Reminder



DenseNet Architecture

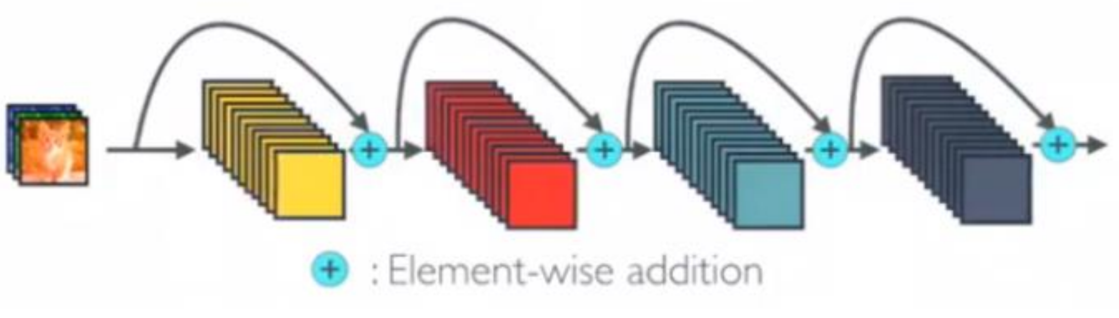
Dense-121. Dx: Dense Block x. Tx: Transition Block x

DenseNet Reminder : Dense Blocks



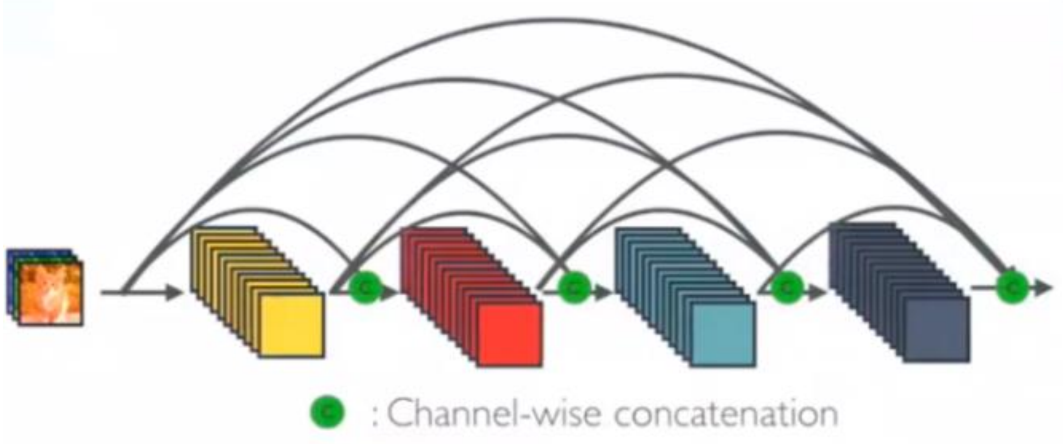
Standard ConvNet Concept

In ***Standard ConvNet***, input image goes through multiple convolution and obtain high-level features



ResNet Concept

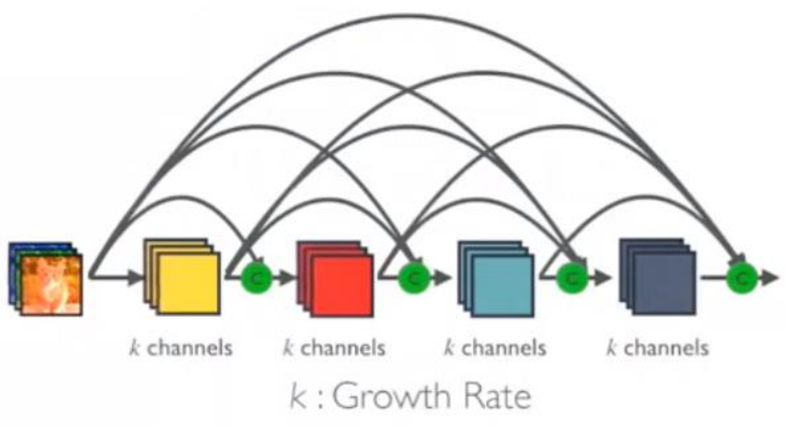
In ***Residual Block concept***, identity mapping is proposed to promote the gradient propagation. Element-wise addition is used.



One Dense Block in DenseNet

In ***DenseNet***, each layer obtains additional inputs from all preceding layers and passes on its own feature-maps to all subsequent layers.

DenseNet Reminder : Dense Blocks



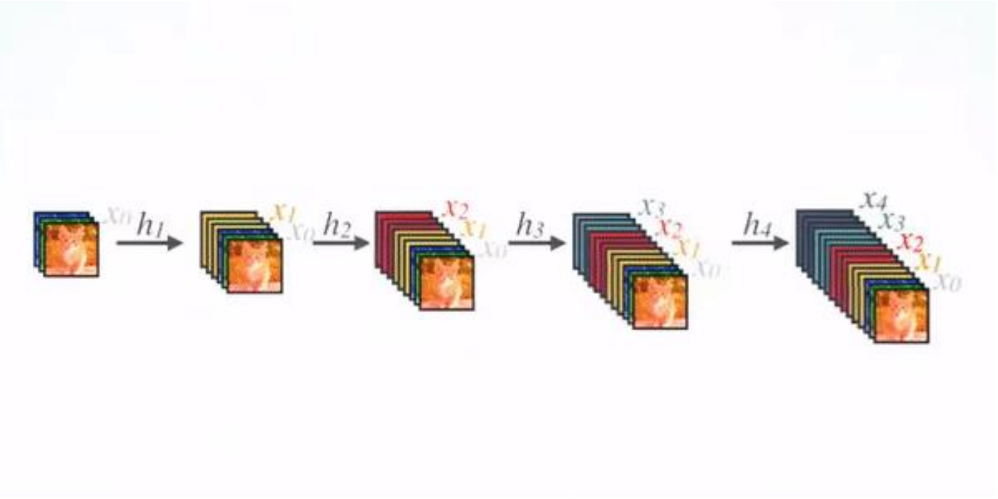
Dense Block in DenseNet with Growth Rate k

Since each layer receives feature maps from all preceding layers, network can be thinner and compact, i.e. number of channels can be fewer

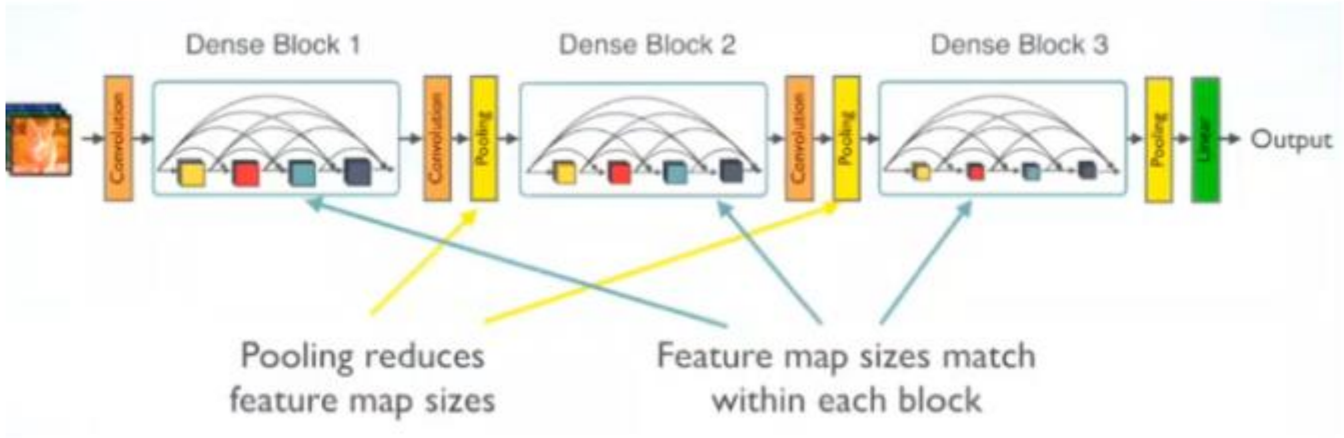
Concatenation during Forward Propagation

$$k_l = k_0 + k * (l - 1)$$

DenseNet Reminder : DenseNet Architecture



Composition Layer



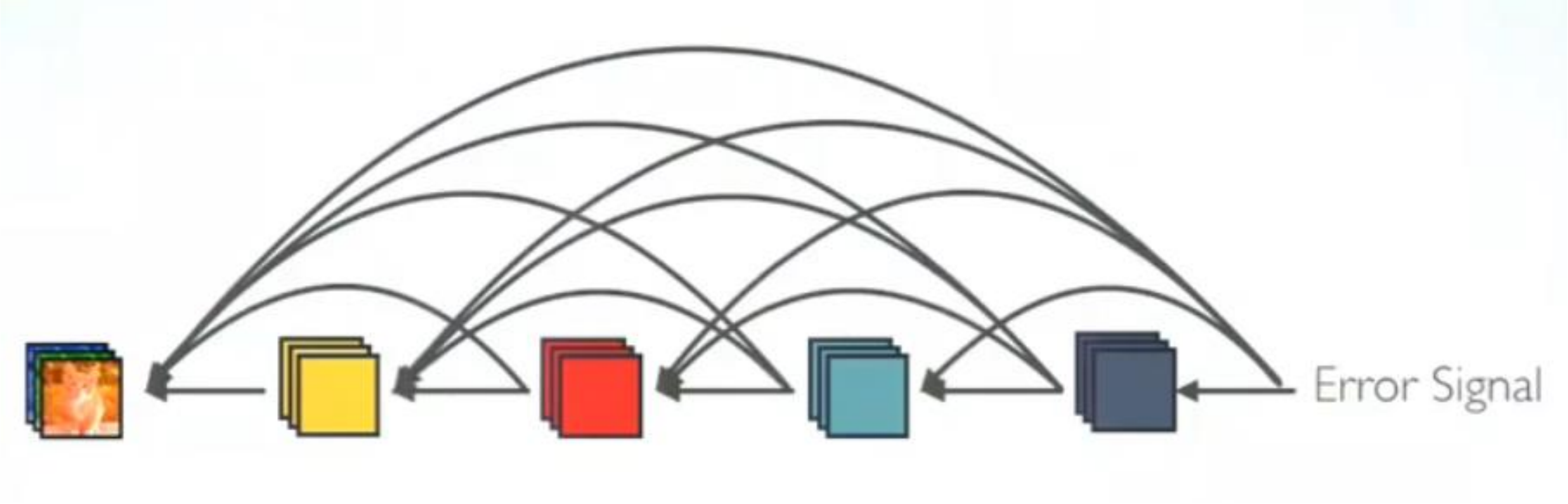
Multiple Dense Blocks

For each composition layer, Pre-Activation Batch Norm (BN) and ReLU, then 3×3 Conv are done with output feature maps of k channels, say for example, to transform $x0$, $x1$, $x2$, $x3$ to $x4$.

- 1×1 Conv followed by 2×2 average pooling are used as the transition layers between two contiguous dense blocks
- Feature map sizes are the same within the dense block so that they can be concatenated together easily.
- At the end of the last dense block, a global average pooling is performed and then a softmax classifier is attached

DenseNet Reminder

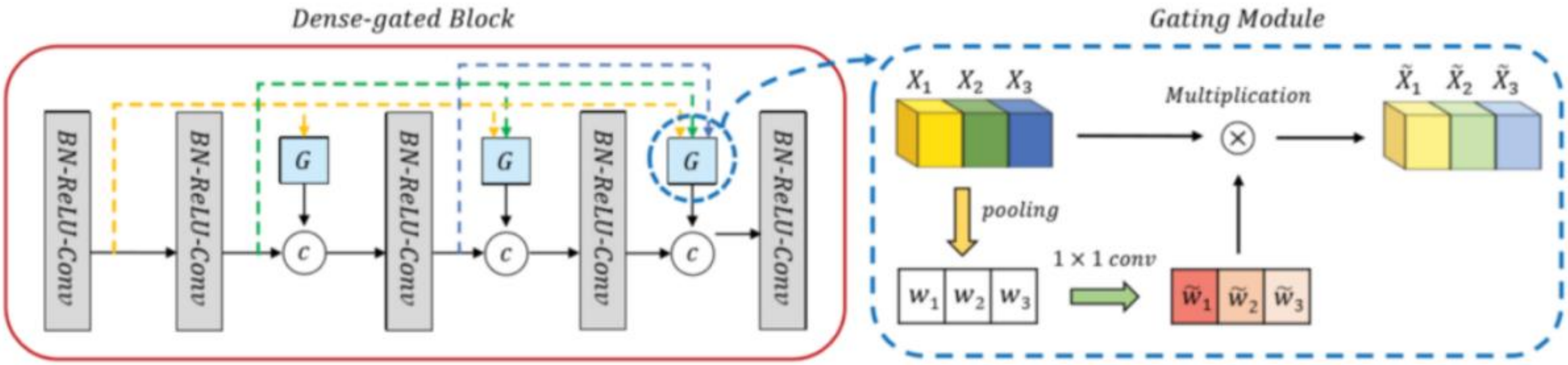
- Advantage : Strong gradient flow



- Drawback : Redundancy

Joseph W. FAYE

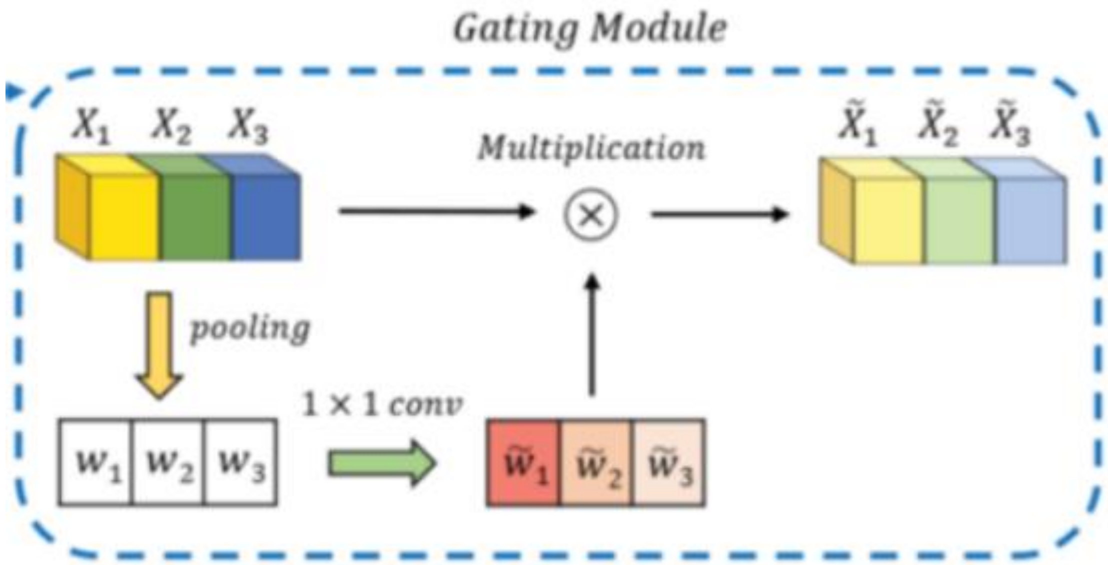
Dense Gated Blocks



Dense-gated Blocks

Dense Gated Blocks : Gating Module

- The original dense connections are changed by **reweighting each feature maps before concatenation** and design a gating module to make the network **focus on more informative feature maps.**
- More precisely, **feature compression is performed and turn each of feature maps concatenated into a layer descriptor.**
- **This layer descriptor has a global receptive field in certain degrees**, and the output dimension matches the number of input characteristic concatenation.



Dense Gated Blocks : Gating Module

For the (l+1)-th layer, a statistic $z \in Rl$ is generated by squeezing the feature maps X and zc as the c-th element of z can be expressed as

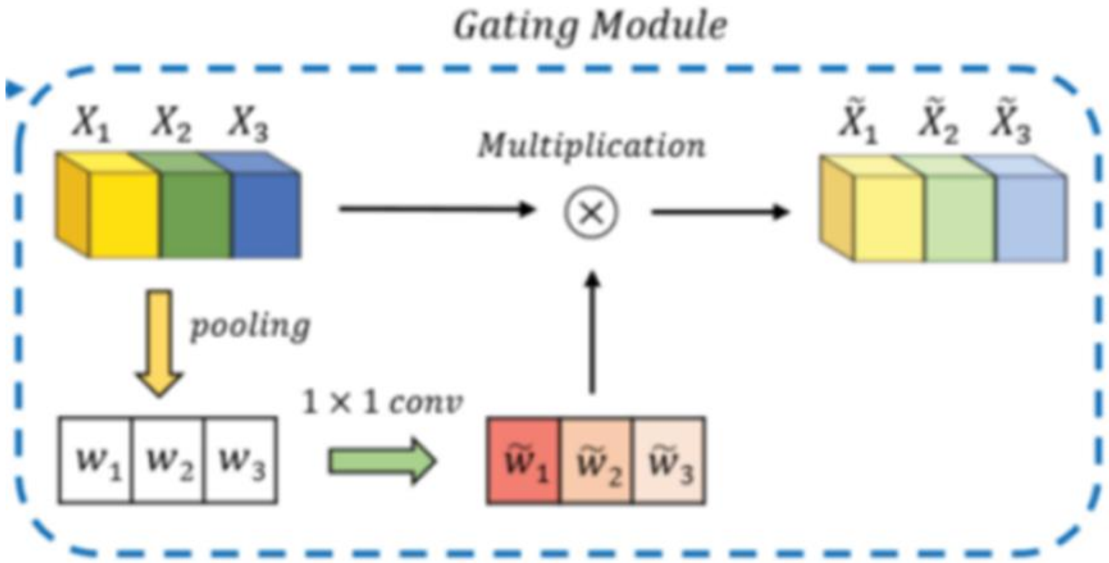
$$z_c = \frac{1}{D_c \times W_c \times H_c} \sum_{i=1}^{D_c} \sum_{j=1}^{W_c} \sum_{k=1}^{H_c} x_c(i,j,k), c \in (0,1,\ldots,l)$$

After applying global average pooling above, then 1×1 convolutional layers Wa and Wb, are used to explicitly model the correlation between different layers.

$$s = \sigma\left(W_b \delta\left(W_a z\right)\right),$$

the final output is a reweight operation

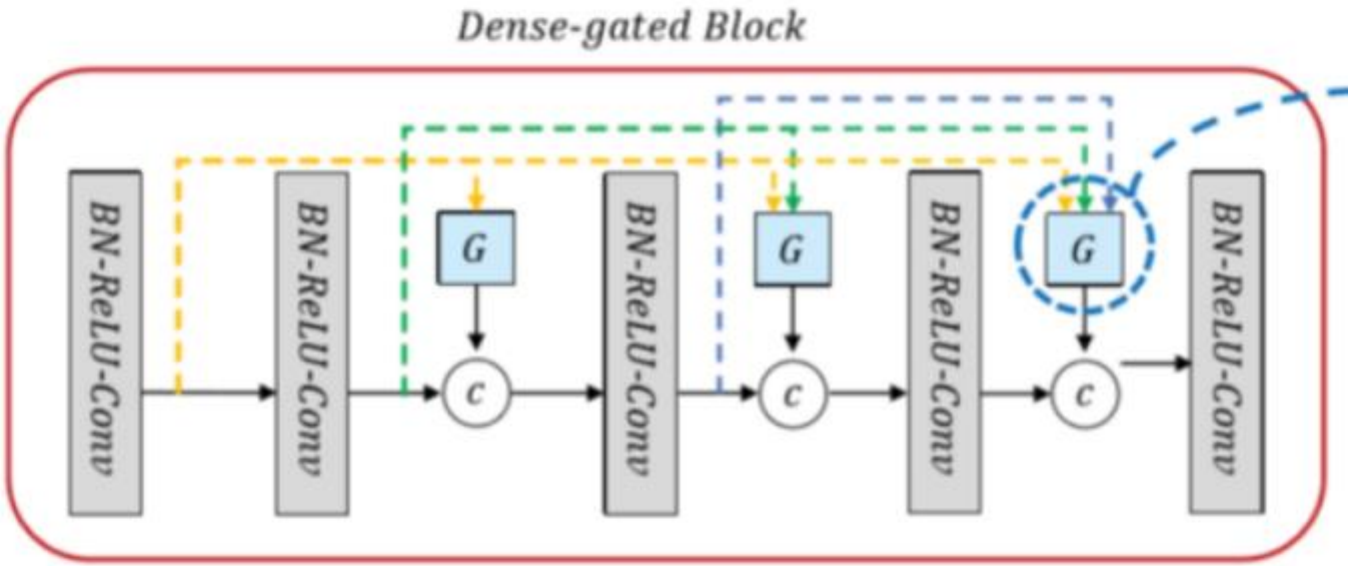
$$\widetilde{x_c} = s_c \odot x_c,$$



Dense Gated Blocks

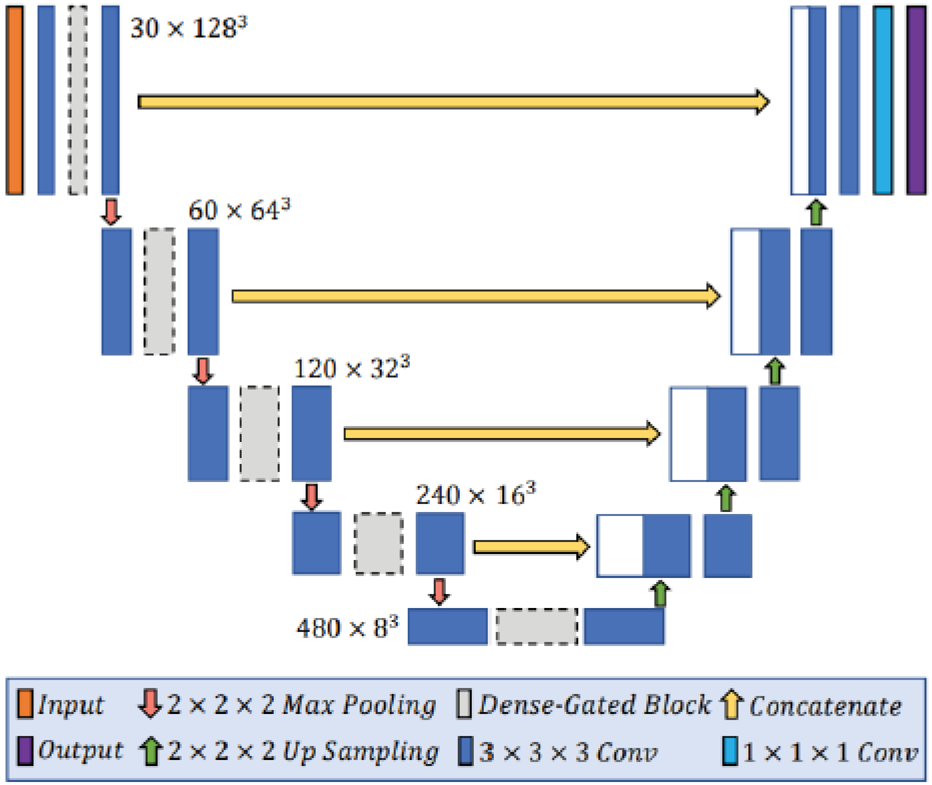
The feature maps are densely connected in a left-right manner within a block. Each dense-gated block has 5 convolutional layers:

$$h_l = [x_0, x_1, \ldots, x_l],$$
$$x_{l+1} = \varphi([x_l, g_l(h_l)]),$$
$$\varphi(x_i) = \mathrm{W} * \delta(\mathrm{B}(x_i)), i \in \{0, \ldots, l\}.$$



This idea is similar to the one in DenseNet

DGNet : Network Architecture



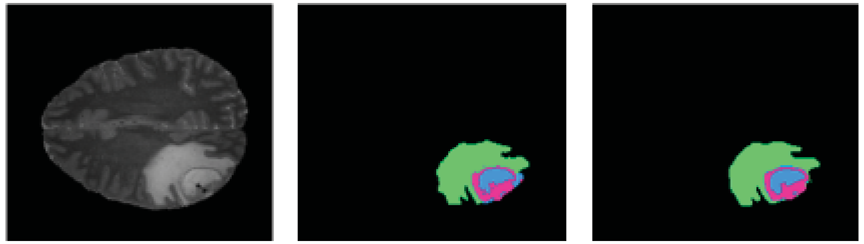
3D U-Net

Experimental Results

BraTS 2018 Dataset

MICCAI BraTS 2018 training set and validation set consist of **ample multi-institutional clinically-acquired and multi-modal MRI scans of glioblastoma (HGG) and lower-grade glioma (LGG).**

input *ground truth* *output*



Method	Dice			Hausdorff95		
	ET	WT	TC	ET	WT	TC
Isensee [10]	0.810	0.908	0.854	**2.540**	4.970	7.040
Myro [11]	0.817	0.907	0.860	3.824	4.412	6.841
McKi [12]	0.796	0.903	0.847	3.550	4.170	4.930
Zhou [13]	0.814	0.909	0.853	2.716	4.172	6.545
Our	**0.818**	**0.912**	**0.862**	2.703	**3.901**	**4.595**
Chen [14]	0.740	0.888	0.844	4.631	5.888	5.661
Isensee [10]	0.772	**0.901**	0.843	3.680	5.610	6.000
Our	**0.830**	0.899	**0.899**	**2.167**	**3.772**	**3.791**
Base	0.771	0.898	0.822	3.223	6.306	9.244
Base+DB	0.798	0.892	0.825	4.894	6.225	8.037
Base+DGB	**0.818**	**0.912**	**0.862**	**2.703**	**3.901**	**4.595**

Top: Validation Set, Middle: Training Set, Bottom: Ablation Study on Validation Set

Hemorrhage Dataset Collected by Authors

It is made up of **intracranial hemorrhage CT images** consisting of 500 collected patients from hospitals. The Annotations include intracranial hemorrhage area (lesion, labeled as 1), while other pixels are all labeled as 0.

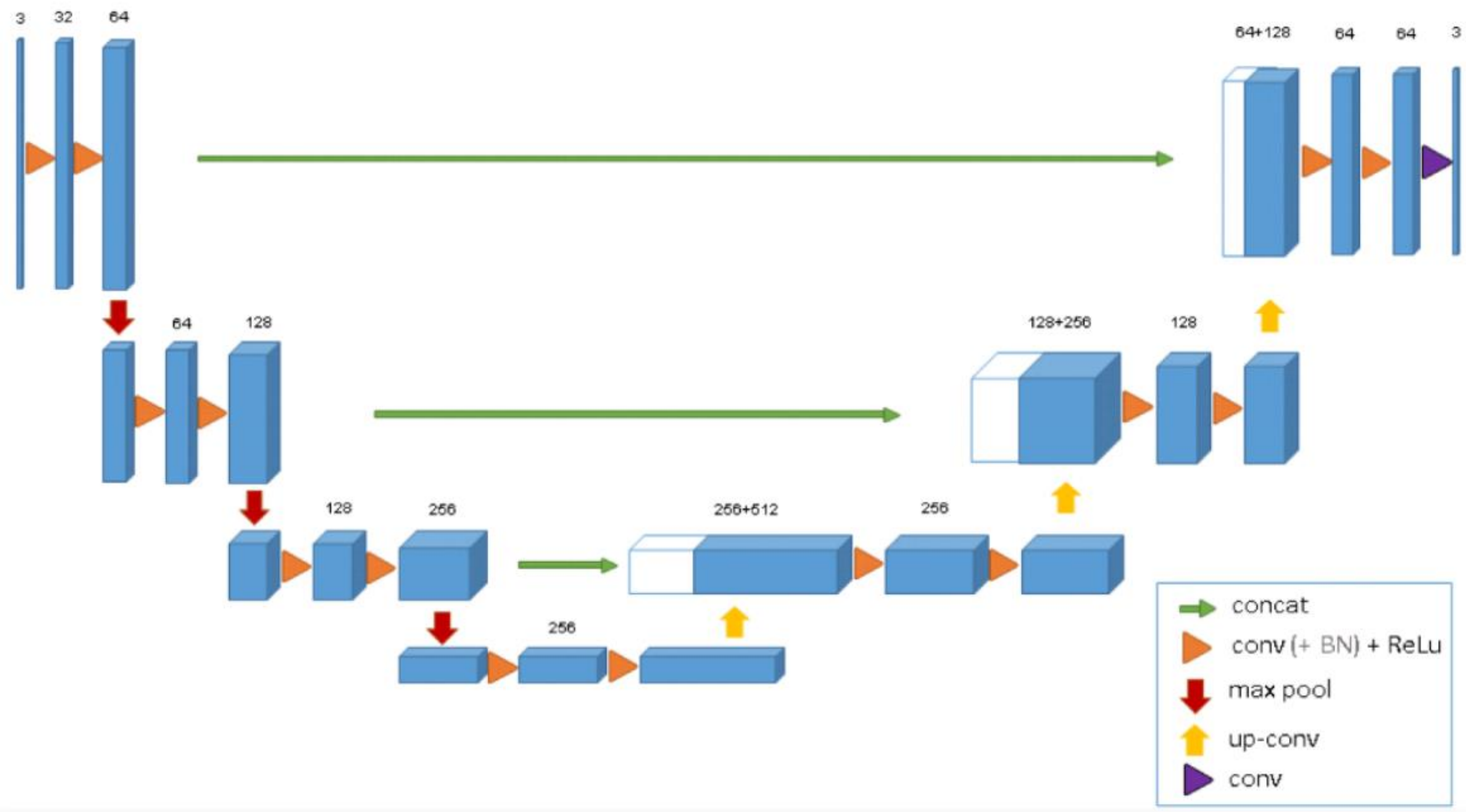
input *ground truth* *output*

Methods	Lesion	Background	mIoU
Base	0.673	0.995	0.834
Base+DB	0.682	0.996	0.839
Base+DGB	**0.692**	0.996	**0.844**
DeepMedic	0.683	**0.997**	0.840
UNet++	0.677	0.995	0.836
DenseASPP	0.670	0.996	0.833
DeepLabv3	0.639	0.995	0.817

IoU Results

Thank you for your attention

Bonus : 3D – UNet



3D U-Net Architecture