

MO-K-DBRA-8

Session: Data Science: Applications in Radiation Therapy
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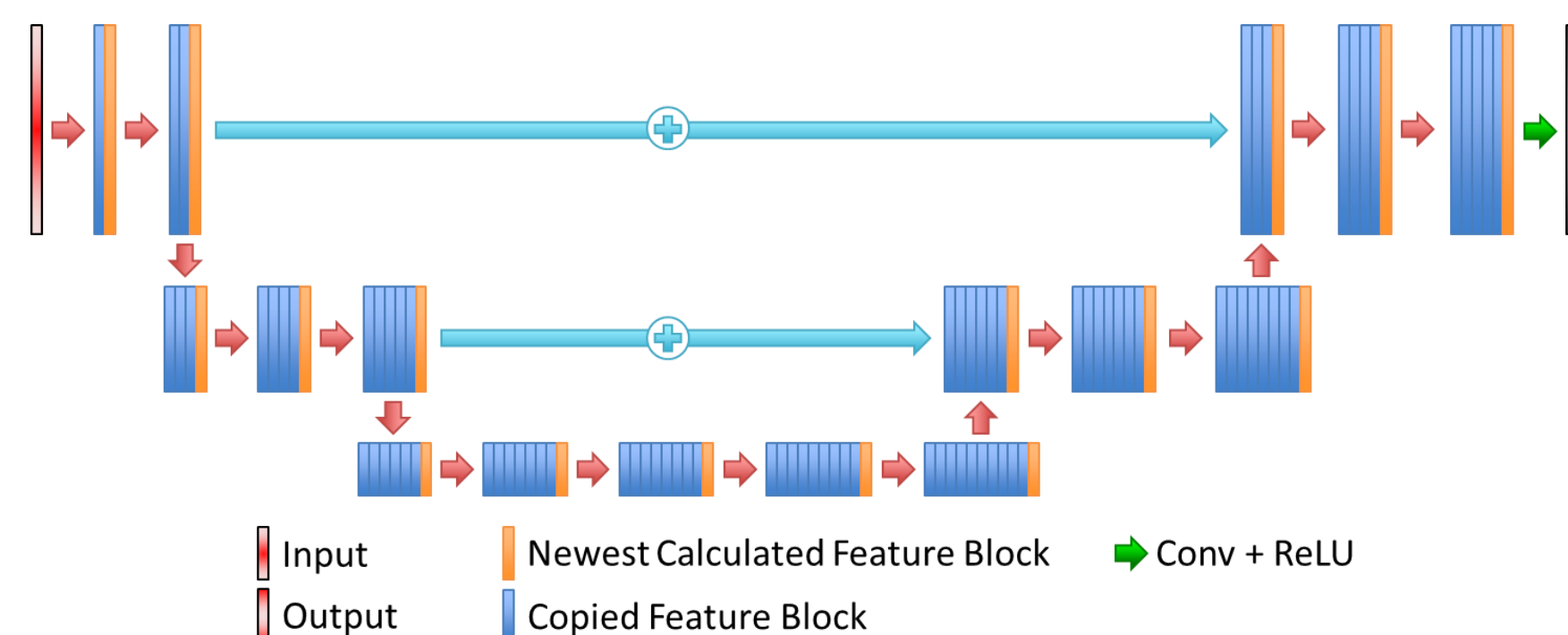
Introduction

- Treatment planning for head and neck (H&N) cancer is regarded as one of the most complicated due to large target volume, multiple prescription dose levels, and many radiation-sensitive critical structures near the target.
- Requires a high level of human expertise and a tremendous amount of effort to produce personalized high quality plans.
- We propose to develop model that can predict 3D clinical dose distributions from contours and prescription dose for H&N cancer patients.
- Can be used as a clinical guidance tool for treatment planners to improve plan quality and planning efficiency.

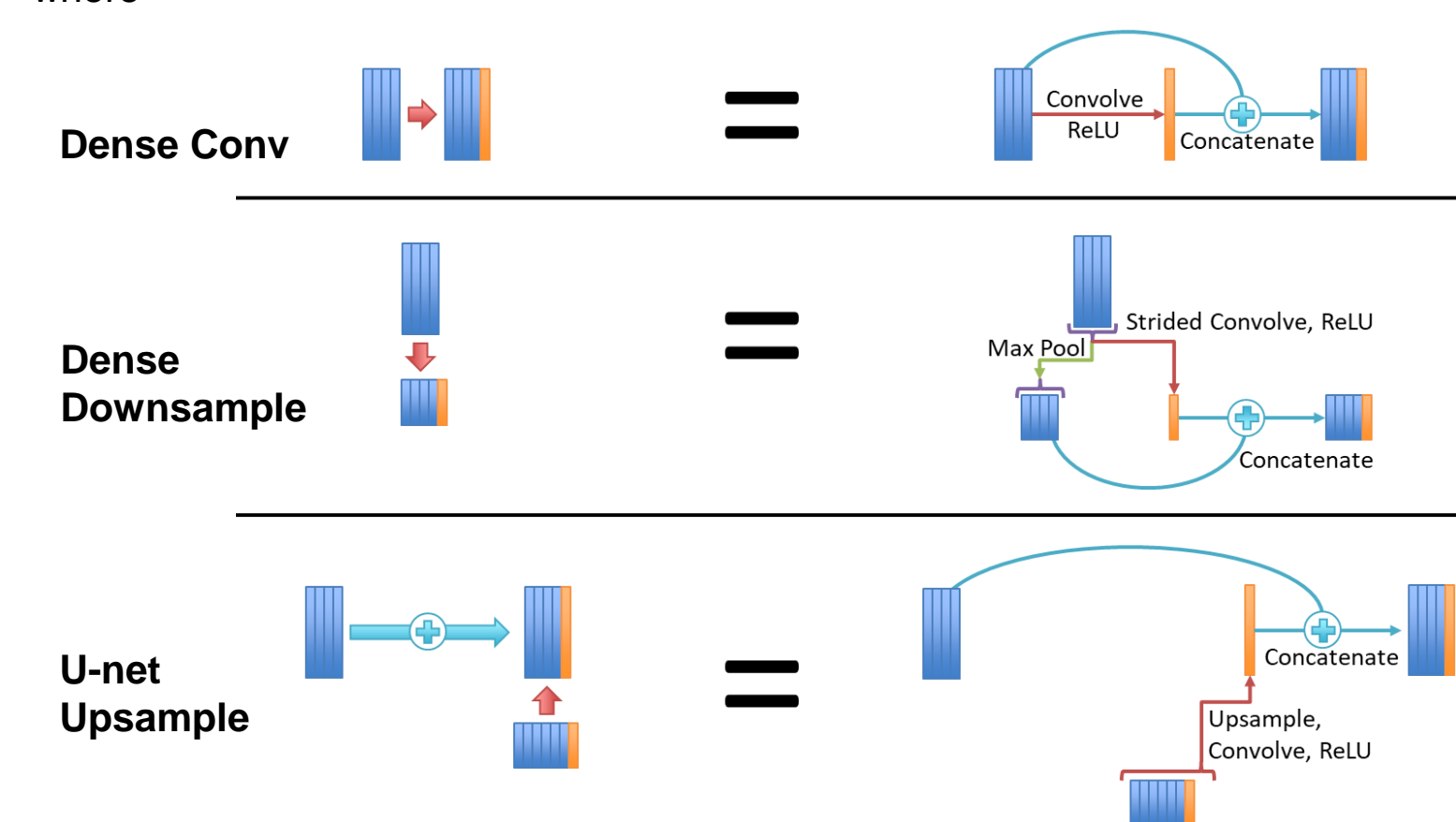
Hierarchically Dense U-net (HD U-net) Architecture

Combines 2 state-of-the-art deep learning models:

- U-net
 - Voxel-to-voxel mapping for 3D data
 - Capable of capturing both global and local information
- DenseNet (CVPR 2017, Best Paper Award)
 - Reduces vanishing gradient problem
 - Strengthen feature propagation
 - Encourage feature reuse
 - Reduces number of necessary trainable parameters

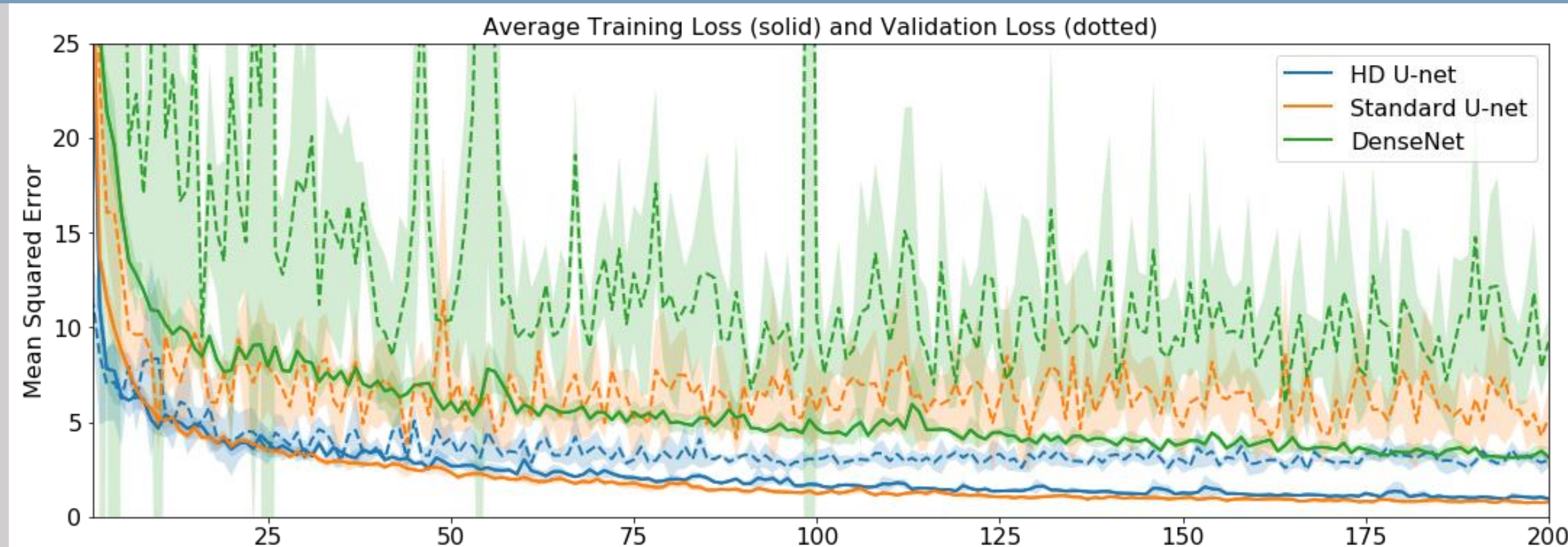


where



Training/Validation/Testing Data

- 120 H&N patients
 - For each patient: 1-5 PTVs with prescription doses ranging from 42.5Gy to 72Gy
 - 20 randomly selected as holdout test data
 - Remaining 100 used for 5-fold cross validation (80 training and 20 validation)
- Input
 - 96 x 96 x 64 (5 mm³) patch randomly selected at each training iteration
 - 22 organs at risk included as masks in separate channels
 - PTV masks assigned their prescription dose and included as a channel
- Output is the predicted dose distribution
 - Mean squared error taken between prediction and reference clinical dose



	HD U-net	Standard U-net	DenseNet			
Trainable parameters	3,289,006	40,068,385	3,361,708			
Prediction time for 1 patient	5.42 ± 1.99 s	4.48 ± 1.67 s	17.12 ± 6.42 s			
Exact model architectures used in study. All layers with "Conv" include ReLU as the nonlinear activation.						
Layer number	Layer type	Number features	Layer type	Number features	Layer type	Number features
1	Input	23	Input	23	Input	23
2	Dense Conv	39	Conv	32	Dense Conv	47
3	Dense Conv	55	Conv	32	Dense Conv	71
4	Dense Downsample	71	Max Pooling	32	Dense Conv	95
5	Dense Conv	87	Conv	64	Dense Conv	119
6	Dense Conv	103	Conv	64	Dense Conv	143
7	Dense Downsample	119	Max Pooling	64	Conv	72
8	Dense Conv	135	Conv	128	Dense Conv	96
9	Dense Conv	151	Conv	128	Dense Conv	120
10	Dense Downsample	167	Max Pooling	128	Dense Conv	144
11	Dense Conv	183	Conv	256	Dense Conv	168
12	Dense Conv	199	Conv	256	Dense Conv	192
13	Dense Downsample	215	Max Pooling	256	Conv	96
14	Dense Conv	231	Conv	512	Dense Conv	120
15	Dense Conv	247	Conv	512	Dense Conv	144
16	Dense Conv	263	Conv	512	Dense Conv	168
17	Dense Conv	279	Conv	512	Dense Conv	192
18	U-net Upsample	263	U-net Upsample	512	Dense Conv	216
19	Dense Conv	279	Conv	256	Conv	108
20	Dense Conv	295	Conv	256	Dense Conv	132
21	U-net Upsample	215	U-net Upsample	256	Dense Conv	156
22	Dense Conv	231	Conv	128	Dense Conv	180
23	Dense Conv	247	Conv	128	Dense Conv	204
24	U-net Upsample	167	U-net Upsample	128	Dense Conv	228
25	Dense Conv	183	Conv	64	Conv	114
26	Dense Conv	199	Conv	64	Dense Conv	138
27	U-net Upsample	119	U-net Upsample	64	Dense Conv	162
28	Dense Conv	135	Conv	32	Dense Conv	186
29	Dense Conv	151	Conv	32	Dense Conv	210
30	Conv	1	Conv	1	Dense Conv	234
31			Conv	117		117
32			Dense Conv	141		141
33			Dense Conv	165		165
34			Dense Conv	189		189
35			Dense Conv	213		213
36			Dense Conv	237		237
37			Conv	119		119
38			Dense Conv	143		143
39			Dense Conv	167		167
40			Dense Conv	191		191
41			Dense Conv	215		215
42			Dense Conv	239		239
43			Conv	120		120
44			Conv	1		1

