An Effective Approach to detect Lung Cancer on CT scan image using Segmentation with Mask Region-based Convolutional Neural Networks

A project report submitted to propose the plan of executing the project by the award of the degree

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ABSTRACT

Lung cancer is one of the most important deadly diseases in the world. The recent estimates provided by the World Health Organization (WHO) says that around 7.6 million deaths worldwide per year due to lung cancer. Moreover, humanity due to cancer are supposed to continue rising, to become around 17 million worldwide in 2030. Discovering lung cancer in the early stage is the only method for its cure. Different methods are available for diagnosis of lung cancer, namely, MRI, isotope, X-ray and CT. CT scan image are not easy to understand, but using CNN with Image Segmentation it is an easy approach to detect Lung cancer. Convolutional neural network (CNN) is one of the deep structured algorithms widely applied to analyze the ability to visualize and extract the hidden texture features of image datasets. The study aims to automatically extract the self-learned features using an end-to-end learning CNN and compares the results with the conventional state-of-art and traditional computer-aided diagnosis system's performance.

First approach will be to build a simple 2D Conv. Network with optimized parameters using the reference of Taguchi method of using an Orthogonal Array (OA) for finding the optimum parameters, reference of an Article ("Using 2D CNN with Taguchi Parametric Optimization for Lung Cancer Recognition from CT Images", by Cheng-Jian Lin, Shiou Jeng and Mei-Kuei Chen, Received: 13 March 2020; Accepted: 7April 2020; Published: 9 April 2020).

After the successful building of this basic 2D-CNN model for classification of Cancer, some more test are planned to do on the as me model which were not included in the previous article such as the depth of the model, use of dropout and some other methods and the results will be analyzed

using Tensor board and selection of the parameters and number of experimental runs will be done using Taguchi Parametric Optimization.

Next, will be the preprocessing of the input image and segmentation of the regions like lungs and the cancer areas for making the model more accurate for the processing and result finding,(Reference of a Journal Pre-proof is taken ("An effective approach for CT lung segmentation using mask region-based convolution neural networks" by Qinhua Hu, Lu´ıs Fabr ´ıcio de F. Souza, Gabriel Bandeira Holanda, Shara S.A. Alves, Francisco H´ercules dos S. Silva, Tao Han, Pedro P. Rebouc¸as Filho) further more networks like the U-Net and Nested U-Net will also be used for the segmentation purpose.

At last both the trained and optimized model will be used and combined to make a complete final model for the classification of lung cancer. Taking reference of a paper "Deep learning for lung Cancer" by A. Asuntha & Andy Srinivasan.

For the input layer, lung nodule CT images are used and being collected for various steps of project. The sources of the datasets will be mentioned in the final project submission report. Images are pre-processed to uniquely segment the nodule region of interest (NROI) in correspondence to four radiologists' annotations and markings describing the coordinates and ground-truth values.

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1.Introduction

A cancer that begins in the lungs and most often occurs in people who smoke. Two major types of lung cancer are non-small cell lung cancer and small cell lung cancer. Causes of lung cancer include smoking, second-hand smoke, exposure to certain toxins and family history. Symptoms include a cough (often with blood), chest pain, wheezing and weight loss. These symptoms often don't appear until the cancer is advanced. Lung cancer is one of the most important deadly diseases in the world. The recent estimates provided by World Health Organization (WHO) says that around 7.6 million deaths worldwide per year due to lung cancer. Moreover, humanity due to cancer are supposed to continue rising, to become around 17 million worldwide in 2030.Early detection can help in curing. Early cancer Detection can be possible by applying deep learning models on CT scan Images.

2. Related Work

In medical field, it is hard and complex to detect specially on CT scanned Images. But methods using CNNs have been widely explored in various studies for the detection and pre-diagnosis of pathologies. Wang used a CNN-based segmentation method in 2D and 3D images on lung CT scans for the diagnosis of diffuse pulmonary disease. Studies to predict survival time among lung cancer patients were carried out, and CNN was used to detect anomalies by scanning the pixels in CT images. Furthermore, the classification and segmentation of the thoracic region was demonstrated and CNNs have been used to automatically detect and segment lung nodules in CT images. Kasi Nathan introduced multi-scale Gaussian filters into his model to detect lung tumors by active contouring using CNN and achieved good results with evaluation metrics of 89.0% for Sensitivity and 91% for Specificity. Liu presented a semi-supervised method for the detection of pulmonary nodules by a convolutional transfer neural network based on data analysis using a modified U-Net model.

3. Taguchi method in 2-D CNN

Currently used Taguchi method which will be used as reference.

In it a $L_{36}(2^{11},3^{12})$ Orthogonal Array is used as experimental design, and 36 experimental runs were generated by Minitab® 19 (Scientific Formosa Inc, Taipei, Taiwan) are given in Table.

Table 1. Levels of control factors.

Columns	Abbreviations	Factors	Level 1	Level 2	Level 3
A	C1_S	conv1_Stride	1	2	
B	C1_P	conv1_padding	0	1	
C	C2_S	conv2_Stride	1	2	
D	C2_P	conv2_padding	0	1	
E	C1_KS	conv1_Kernel size	3	5	7
F	C1_F	conv1_Filter	4	6	12
G	C2_KS	conv2_Kernel size	3	5	7
H	C2_F	conv2_Filter	8	16	32

Table 2. L_{36} orthogonal array (OA) for experiments the parameters setting.

Exp. No	Factor							
	C1_S A	C1_P B	C2_S C	C2_P D	C1_KS E	C1_F F	C2_KS G	C2_F H
1	1	0	1	0	3	4	3	8
2	1	0	1	0	5	6	5	16
3	1	0	1	0	7	12	7	32
4	1	0	1	0	3	4	3	8
5	1	0	1	0	5	6	5	16
6	1	0	1	0	7	12	7	32
7	1	0	2	1	3	4	5	32
8	1	0	2	1	5	6	7	8
9	1	0	2	1	7	12	3	16
10	1	1	1	1	3	4	7	16
11	1	1	1	1	5	6	3	32
12	1	1	1	1	7	12	5	8
13	1	1	2	0	3	6	7	8
14	1	1	2	0	5	12	3	16
15	1	1	2	0	7	4	5	32
16	1	1	2	1	3	6	7	16
17	1	1	2	1	5	12	3	32
18	1	1	2	1	7	4	5	8
19	2	0	2	1	3	6	3	32
20	2	0	2	1	5	12	5	8
21	2	0	2	1	7	4	7	16
22	2	0	2	0	3	6	5	32
23	2	0	2	0	5	12	7	8
24	2	0	2	0	7	4	3	16
25	2	0	1	1	3	12	5	8
26	2	0	1	1	5	4	7	16
27	2	0	1	1	7	6	3	32
28	2	1	2	0	3	12	5	16
29	2	1	2	0	5	4	7	32
30	2	1	2	0	7	6	3	8
31	2	1	1	1	3	12	7	32
32	2	1	1	1	5	4	3	8
33	2	1	1	1	7	6	5	16
34	2	1	1	0	3	12	3	16
35	2	1	1	0	5	4	5	32
36	2	1	1	0	7	6	7	8

The important results generated from the experimental runs are:

Table 4. The signal-to-noise (S/N) ratios of accuracy for different combinations of factors and levels.

Run#	Factor								Result				
	A C1_S	B C1_P	C C2_S	D C2_P	E C1_KS	F C1_F	G C2_KS	H C2_F	Y_1 (%)	Y_2 (%)	Y_3 (%)	Y_{ave} (%)	S/N (Y)
1	1	0	1	0	3	4	3	8	97.19	90.45	93.06	93.57	−0.498
2	1	0	1	0	5	6	5	16	87.84	93.97	95.10	92.30	−0.725
3	1	0	1	0	7	12	7	32	94.70	88.85	89.66	91.07	−0.741
4	1	0	1	0	3	4	3	8	94.58	96.80	95.00	95.46	−0.405
5	1	0	1	0	5	6	5	16	95.10	88.59	92.19	91.96	−0.739
6	1	0	1	0	7	12	7	32	91.06	92.96	94.19	92.74	−0.657
7	1	0	2	1	3	4	5	32	97.47	97.77	96.66	97.30	−0.238
8	1	0	2	1	5	6	7	8	90.21	86.67	94.70	90.53	−0.882
9	1	0	2	1	7	12	3	16	92.51	92.21	90.04	91.59	−0.765
10	1	1	1	1	3	4	7	16	96.58	92.25	96.46	95.10	−0.443
11	1	1	1	1	5	6	3	32	98.10	97.88	98.68	98.22	−0.156
12	1	1	1	1	7	12	5	8	88.65	80.98	85.05	84.89	−1.440
13	1	1	2	0	3	6	7	8	86.69	91.24	91.00	89.64	−0.957
14	1	1	2	0	5	12	3	16	88.08	92.33	92.07	90.83	−0.842
15	1	1	2	0	7	4	5	32	97.21	97.27	92.57	95.68	−0.390
16	1	1	2	1	3	6	7	16	91.50	93.77	98.00	94.42	−0.509
17	1	1	2	1	5	12	3	32	98.64	93.71	99.43	97.26	−0.250
18	1	1	2	1	7	4	5	8	88.47	77.28	83.02	82.92	−1.666
19	2	0	2	1	3	6	3	32	95.83	96.66	96.14	96.21	−0.336
20	2	0	2	1	5	12	5	8	83.79	84.42	80.15	82.79	−1.648
21	2	0	2	1	7	4	7	16	93.38	96.32	92.53	94.08	−0.534
22	2	0	2	0	3	6	5	32	95.67	94.86	96.26	95.60	−0.392
23	2	0	2	0	5	12	7	8	85.17	89.66	83.69	86.17	−1.304
24	2	0	2	0	7	4	3	16	81.06	85.29	81.28	82.54	−1.673
25	2	0	1	1	3	12	5	8	92.76	91.24	92.65	92.22	−0.705
26	2	0	1	1	5	4	7	16	92.51	92.09	92.03	92.21	−0.705
27	2	0	1	1	7	6	3	32	96.11	96.72	94.88	95.90	−0.364
28	2	1	2	0	3	12	5	16	90.79	87.05	85.69	87.84	−1.134
29	2	1	2	0	5	4	7	32	96.46	91.68	94.80	94.31	−0.514
30	2	1	2	0	7	6	3	8	80.41	77.09	77.36	78.29	−2.131
31	2	1	1	1	3	12	7	32	97.86	98.44	99.13	98.48	−0.134
32	2	1	1	1	5	4	3	8	93.10	95.08	92.51	93.56	−0.580
33	2	1	1	1	7	6	5	16	89.58	81.99	81.26	84.28	−1.511
34	2	1	1	0	3	12	3	16	94.70	92.03	91.12	92.62	−0.670
35	2	1	1	0	5	4	5	32	96.84	97.81	92.78	95.81	−0.379
36	2	1	1	0	7	6	7	8	82.70	87.11	86.32	85.38	−1.380

Table 5. Mean responses of the S/N ratios for each level and optimal parameter for the LIDC-IDRI dataset.

Level	Factors							
	A **C1_S**	**B** **C1_P**	**C** **C2_S**	**D** **C2_P**	**E** **C1_KS**	**F** **C1_F**	**G** **C2_KS**	**H** **C2_F**
1	−0.7002	−0.7672	−0.6953	−0.9153	−0.5467	−0.6927	−0.7514	−1.199
2	−0.8939	−0.8381	−0.898	−0.7147	−0.7258	−0.8493	−0.9297	−0.8646
3					−1.1451	−0.8756	−0.7365	−0.354
Delta	0.1938	0.0708	0.2028	0.2006	0.5985	0.1829	0.1933	0.845
Rank	5	8	3	4	2	7	6	1
Best level	1	1	1	2	1	1	3	3
Optimal parameter	1	0	1	1	3	4	7	32

4. Result of Lung cancer Detection Algorithm Comparison

1) Segmentation approaches:

Table 10 Overlap measures obtained by K-Mean, FCM, Ant Colony and ABC

Data sets	Segmentation Approaches			
	K-Means	FCM	Ant Colony	ABC
TrTeD1	0.805	0.884	0.913	0.933
TrTeD2	0.821	0.9	0.929	0.949
TrTeD3	0.832	0.911	0.94	0.96
TrTeD4	0.85	0.929	0.958	0.978
TrTeD5	0.795	0.874	0.903	0.923
TrTeD6	0.811	0.89	0.919	0.939
TrTeD7	0.822	0.901	0.93	0.95
TrTeD8	0.84	0.919	0.948	0.968
TrTeD9	0.796	0.875	0.904	0.924
TrTeD10	0.812	0.891	0.92	0.94
TrTeD11	0.823	0.902	0.931	0.951
TrTeD12	0.841	0.92	0.949	0.969
TrTeD13	0.786	0.865	0.894	0.914
TrTeD14	0.802	0.881	0.91	0.93
TrTeD15	0.813	0.892	0.921	0.941
TrTeD16	0.831	0.91	0.939	0.959

2) Feature Extraction using Open-CV /IP

Table 11 Analysis of Average accuracy, sensitivity, specificity and Error Rate of Real-time Dataset for Feature Extraction Approaches

Metrics	Accuracy	Sensitivity	Specificity	Error Rate	Accuracy	Sensitivity	Specificity	Error Rate
	TrTeD1				TrTeD2			
Intensity	82.23	91.13	94.35	17.77	82.232	91.132	94.352	17.772
HOG	83.14	92.15	93.52	16.86	83.142	92.152	93.522	16.862
Wavelet	83.66	90.74	94.74	16.34	83.662	90.742	94.742	16.342
LBP	82.58	91.4	93.91	17.42	82.582	91.402	93.912	17.422
SIFT	81.12	90.51	92.85	18.88	81.122	90.512	92.852	18.882
Zernike	82.71	89.82	93.8	17.29	82.712	89.822	93.802	17.292
Eccentricity	81.6	90.53	92.62	18.4	81.602	90.532	92.622	18.402
Curvature	80.28	89.64	91.28	19.72	80.282	89.642	91.282	19.722
Proposed	97.47	98.11	97.77	2.53	97.472	98.112	97.772	2.532
	TrTeD3				TrTeD4			
Intensity	82.252	91.152	94.372	17.792	82.273	91.173	94.393	17.813
HOG	83.162	92.172	93.542	16.882	83.183	92.193	93.563	16.903
Wavelet	83.682	90.762	94.762	16.362	83.703	90.783	94.783	16.383
LBP	82.602	91.422	93.932	17.442	82.623	91.443	93.953	17.463
SIFT	81.142	90.532	92.872	18.902	81.163	90.553	92.893	18.923
Zernike	82.732	89.842	93.822	17.312	82.753	89.863	93.843	17.333
Eccentricity	81.622	90.552	92.642	18.422	81.643	90.573	92.663	18.443
Curvature	80.302	89.662	91.302	19.742	80.323	89.683	91.323	19.763
Proposed	97.492	98.132	97.792	2.552	97.513	98.153	97.813	2.573
	TrTeD5				TrTeD6			
Intensity	82.033	90.933	94.153	17.967	81.853	90.753	93.973	18.147
HOG	82.943	91.953	93.323	17.057	82.763	91.773	93.143	17.237
Wavelet	83.463	90.543	94.543	16.537	83.283	90.363	94.363	16.717
LBP	82.383	91.203	93.713	17.617	82.203	91.023	93.533	17.797
SIFT	80.923	90.313	92.653	19.077	80.743	90.133	92.473	19.257
Zernike	82.513	89.623	93.603	17.487	82.333	89.443	93.423	17.667
Eccentricity	81.403	90.333	92.423	18.597	81.223	90.153	92.243	18.777
Curvature	80.083	89.443	91.083	19.917	79.903	89.263	90.903	20.097
Proposed	97.273	97.913	97.573	2.727	97.093	97.733	97.393	2.907
	TrTeD7				TrTeD8			
Intensity	81.623	90.523	93.743	18.377	81.783	90.683	93.903	18.217
HOG	82.533	91.543	92.913	17.467	82.693	91.703	93.073	17.307
Wavelet	83.053	90.133	94.133	16.947	83.213	90.293	94.293	16.787
LBP	81.973	90.793	93.303	18.027	82.133	90.953	93.463	17.867
SIFT	80.513	89.903	92.243	19.487	80.673	90.063	92.403	19.327
Zernike	82.103	89.213	93.193	17.897	82.263	89.373	93.353	17.737
Eccentricity	80.993	89.923	92.013	19.007	81.153	90.083	92.173	18.847
Curvature	79.673	89.033	90.673	20.327	79.833	89.193	90.833	20.167
Proposed	96.863	97.503	97.163	3.137	97.023	97.663	97.323	2.977
	TrTeD9				TrTeD10			
Intensity	81.873	90.773	93.993	18.127	81.863	90.763	93.983	18.137
HOG	82.783	91.793	93.163	17.217	82.773	91.783	93.153	17.227
Wavelet	83.303	90.383	94.383	16.697	83.293	90.373	94.373	16.707
LBP	82.223	91.043	93.553	17.777	82.213	91.033	93.543	17.787
SIFT	80.763	90.153	92.493	19.237	80.753	90.143	92.483	19.247
Zernike	82.353	89.463	93.443	17.647	82.343	89.453	93.433	17.657
Eccentricity	81.243	90.173	92.263	18.757	81.233	90.163	92.253	18.767
Curvature	79.923	89.283	90.923	20.077	79.913	89.273	90.913	20.087
Proposed	97.113	97.753	97.413	2.887	97.103	97.743	97.403	2.897
	TrTeD11				TrTeD12			
Intensity	81.893	90.793	94.013	18.107	81.953	90.853	94.073	18.047
HOG	82.803	91.813	93.183	17.197	82.863	91.873	93.243	17.137
Wavelet	83.323	90.403	94.403	16.677	83.383	90.463	94.463	16.617
LBP	82.243	91.063	93.573	17.757	82.303	91.123	93.633	17.697

Table 11 (continued)

Metrics	Accuracy	Sensitivity	Specificity	Error Rate	Accuracy	Sensitivity	Specificity	Error Rate
SIFT	80.783	90.173	92.513	19.217	80.843	90.233	92.573	19.157
Zernike	82.373	89.483	93.463	17.627	82.433	89.543	93.523	17.567
Eccentricity	81.263	90.193	92.283	18.737	81.323	90.253	92.343	18.677
Curvature	79.943	89.303	90.943	20.057	80.003	89.363	91.003	19.997
Proposed	97.133	97.773	97.433	2.867	97.193	97.833	97.493	2.807
	TrTeD13				TrTeD14			
Intensity	81.973	90.873	94.093	18.027	81.903	90.803	94.023	18.097
HOG	82.883	91.893	93.263	17.117	82.813	91.823	93.193	17.187
Wavelet	83.403	90.483	94.483	16.597	83.333	90.413	94.413	16.667
LBP	82.323	91.143	93.653	17.677	82.253	91.073	93.583	17.747
SIFT	80.863	90.253	92.593	19.137	80.793	90.183	92.523	19.207
Zernike	82.453	89.563	93.543	17.547	82.383	89.493	93.473	17.617
Eccentricity	81.343	90.273	92.363	18.657	81.273	90.203	92.293	18.727
Curvature	80.023	89.383	91.023	19.977	79.953	89.313	90.953	20.047
Proposed	97.213	97.853	97.513	2.787	97.143	97.783	97.443	2.857
	TrTeD15				TrTeD16			
Intensity	81.933	90.833	94.053	18.067	81.973	90.873	94.093	18.027
HOG	82.843	91.853	93.223	17.157	82.883	91.893	93.263	17.117
Wavelet	83.363	90.443	94.443	16.637	83.403	90.483	94.483	16.597
LBP	82.283	91.103	93.613	17.717	82.323	91.143	93.653	17.677
SIFT	80.823	90.213	92.553	19.177	80.863	90.253	92.593	19.137
Zernike	82.413	89.523	93.503	17.587	82.453	89.563	93.543	17.547
Eccentricity	81.303	90.233	92.323	18.697	81.343	90.273	92.363	18.657
Curvature	79.983	89.343	90.983	20.017	80.023	89.383	91.023	19.977
Proposed	97.173	97.813	97.473	2.827	97.213	97.853	97.513	2.787

data set with 0.929 values. ABC has obtained 0.923 value for TrTeD5 data set while K-means, FCM and Ant colony provides less results.

3) Future Extraction Using ML/DL

Table 12 Analysis of Average accuracy, sensitivity, specificity and Error Rate of Real-time Dataset for Classifier Approaches

Metrics	Accuracy	Sensitivity	Specificity	Error Rate	Accuracy	Sensitivity	Specificity	Error Rate
	TrTeD1				TrTeD2			
SVM	94.23	95.61	94.91	5.77	94.25	95.63	94.93	5.75
Bagging	89.26	90.75	89.95	10.74	89.28	90.77	89.97	10.72
Naive Bayes	85.71	86.63	86.42	14.29	85.73	86.65	86.44	14.27
KNN	84.23	85.21	84.96	15.77	84.25	85.23	84.98	15.75
AdaBoost	91.76	92.82	92.43	8.24	91.78	92.84	92.45	8.22
ELM	97.14	98.39	97.87	2.86	97.16	98.41	97.89	2.84
CNN	98.18	98.43	98.76	1.82	98.21	98.46	98.79	1.79
GACNN	98.76	98.88	98.93	1.24	98.79	98.91	98.96	1.21
PSOCNN	98.91	98.95	98.99	1.09	98.94	98.98	99.02	1.06
FPSOCNN	99.23	99.31	99.43	0.77	99.13	99.24	99.36	0.87
	TrTeD3				TrTeD4			
SVM	94.272	95.652	94.952	5.728	94.291	95.671	94.971	5.709
Bagging	89.302	90.792	89.992	10.698	89.321	90.811	90.011	10.679
Naive Bayes	85.752	86.672	86.462	14.248	85.771	86.691	86.481	14.229
KNN	84.272	85.252	85.002	15.728	84.291	85.271	85.021	15.709
AdaBoost	91.802	92.862	92.472	8.198	91.821	92.881	92.491	8.179
ELM	97.182	98.432	97.912	2.818	97.201	98.451	97.931	2.799
CNN	98.2	98.45	98.78	1.8	98.18	98.43	98.76	1.82
GACNN	98.78	98.9	98.95	1.22	98.76	98.88	98.93	1.24
PSOCNN	98.93	98.97	99.01	1.07	98.91	98.95	98.99	1.09
FPSOCNN	99.12	99.23	99.35	0.88	99.1	99.21	99.33	0.9
	TrTeD5				TrTeD6			
SVM	94.161	94.971	94.841	5.839	94.051	94.861	94.731	5.949
Bagging	89.191	90.011	89.881	10.809	89.081	89.901	89.771	10.919
Naive Bayes	85.641	86.481	86.351	14.359	85.531	86.371	86.241	14.469
KNN	84.161	85.021	84.891	15.839	84.051	84.911	84.781	15.949
AdaBoost	91.691	92.491	92.361	8.309	91.581	92.381	92.251	8.419
ELM	97.071	97.931	97.801	2.929	96.961	97.821	97.691	3.039
CNN	98.05	98.76	98.63	1.95	97.94	98.65	98.52	2.06
GACNN	98.63	98.93	98.8	1.37	98.52	98.82	98.69	1.48
PSOCNN	98.78	98.99	98.86	1.22	98.67	98.88	98.75	1.33
FPSOCNN	99.18	99.33	99.2	0.82	99.07	99.22	99.09	0.93
	TrTeD7				TrTeD8			
SVM	94.121	94.931	94.801	5.879	94.171	94.981	94.851	5.829
Bagging	89.151	89.971	89.841	10.849	89.201	90.021	89.891	10.799
Naive Bayes	85.601	86.441	86.311	14.399	85.651	86.491	86.361	14.349
KNN	84.121	84.981	84.851	15.879	84.171	85.031	84.901	15.829
AdaBoost	91.651	92.451	92.321	8.349	91.701	92.501	92.371	8.299
ELM	97.031	97.891	97.761	2.969	97.081	97.941	97.811	2.919
CNN	98.01	98.72	98.59	1.99	98.06	98.77	98.64	1.94
GACNN	98.59	98.89	98.76	1.41	98.64	98.94	98.81	1.36
PSOCNN	98.74	98.95	98.82	1.26	98.79	99	98.87	1.21
FPSOCNN	99.14	99.29	99.16	0.86	99.19	99.34	99.21	0.81
	TrTeD9				TrTeD10			
SVM	94.291	95.101	94.971	5.709	94.221	95.031	94.901	5.779
Bagging	89.321	90.141	90.011	10.679	89.251	90.071	89.941	10.749
Naive Bayes	85.771	86.611	86.481	14.229	85.701	86.541	86.411	14.299
KNN	84.291	85.151	85.021	15.709	84.221	85.081	84.951	15.779
AdaBoost	91.821	92.621	92.491	8.179	91.751	92.551	92.421	8.249
ELM	97.201	98.061	97.931	2.799	97.131	97.991	97.861	2.869
CNN	98.18	98.89	98.76	1.82	98.11	98.82	98.69	1.89
GACNN	98.76	99.06	98.93	1.24	98.69	98.99	98.86	1.31
PSOCNN	98.91	99.12	98.99	1.09	98.84	99.05	98.92	1.16
FPSOCNN	99.31	99.46	99.33	0.69	99.24	99.39	99.26	0.76

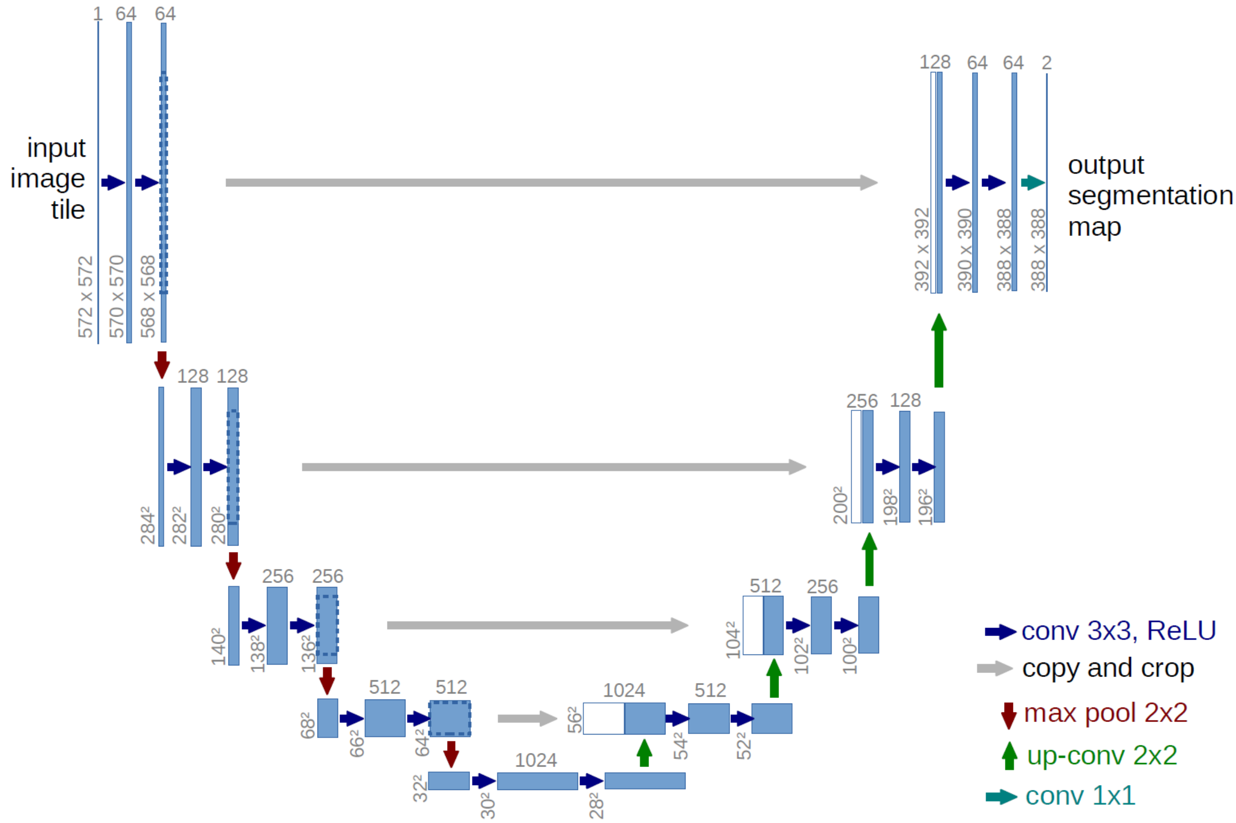
Table 12 (continued)

Metrics	Accuracy	Sensitivity	Specificity	Error Rate	Accuracy	Sensitivity	Specificity	Error Rate
	TrTeD11				TrTeD12			
SVM	94.171	94.981	94.851	5.829	94.141	94.951	94.821	5.829
Bagging	89.201	90.021	89.891	10.799	89.171	89.991	89.861	10.799
Naive Bayes	85.651	86.491	86.361	14.349	85.621	86.461	86.331	14.349
KNN	84.171	85.031	84.901	15.829	84.141	85.001	84.871	15.829
AdaBoost	91.701	92.501	92.371	8.299	91.671	92.471	92.341	8.299
ELM	97.081	97.941	97.811	2.919	97.051	97.911	97.781	2.919
CNN	98.06	98.77	98.64	1.94	98.03	98.74	98.61	1.94
GACNN	98.64	98.94	98.81	1.36	98.61	98.91	98.78	1.36
PSOCNN	98.79	99	98.87	1.21	98.76	98.97	98.84	1.21
FPSOCNN	99.19	99.34	99.21	0.81	99.16	99.31	99.21	0.81
	TrTeD13				TrTeD14			
SVM	94.141	94.951	94.821	5.859	94.141	94.951	94.821	5.859
Bagging	89.171	89.991	89.861	10.829	89.171	89.991	89.861	10.829
Naive Bayes	85.621	86.461	86.331	14.379	85.621	86.461	86.331	14.379
KNN	84.141	85.001	84.871	15.859	84.141	85.001	88.876	15.859
AdaBoost	91.671	92.471	92.341	8.329	91.671	92.471	92.341	8.329
ELM	97.051	97.911	97.781	2.949	97.051	97.911	97.781	2.949
CNN	98.03	98.74	98.61	1.97	98.03	98.74	98.61	1.97
GACNN	98.61	98.91	98.78	1.39	98.61	98.91	98.78	1.39
PSOCNN	98.76	98.97	98.84	1.24	98.76	98.94	98.84	1.24
FPSOCNN	99.16	99.31	99.18	0.84	99.16	99.31	99.19	0.84
	TrTeD15				TrTeD16			
SVM	94.121	94.931	94.801	5.879	94.141	94.951	94.821	5.859
Bagging	89.151	89.971	89.841	10.849	89.171	89.991	89.861	10.829
Naive Bayes	85.601	86.441	86.311	14.399	85.621	86.461	86.331	14.379
KNN	84.121	84.981	84.851	15.879	84.141	85.001	84.871	15.859
AdaBoost	91.651	92.451	92.321	8.349	91.671	92.471	92.341	8.329
ELM	97.031	97.891	97.761	2.969	97.051	97.911	97.781	2.949
CNN	98.01	98.72	98.59	1.99	98.03	98.74	98.61	1.97
GACNN	98.59	98.89	98.76	1.41	98.61	98.91	98.78	1.39
PSOCNN	98.74	98.95	98.82	1.26	98.76	98.97	98.84	1.24
FPSOCNN	99.14	99.29	99.16	0.86	99.16	99.31	99.18	0.84

5. Image Segmentation with U-Net

U-Net is a fully convolutional network (FCN) that does image segmentation. Its goal is to predict each pixel's class. U-Net is built upon the FCN and modified in a way that it yields better segmentation in medical imaging. U-Net architecture has three parts Down sampling , Up sampling and Bottleneck. The U-Net combines the location information from the down sampling path to finally obtain a general information combining localization and context, which is necessary to predict a good segmentation map. No Dense layer is used, so image sizes can be used.

U-Net Architecture -

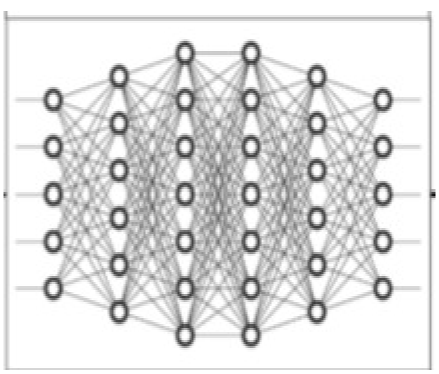


Advanced Version Of U-net will also be tested for segmentation like U-net++/Nested U-Net, and Attention U-Net.

6. Deep Convolutional Neural Network-

In deep learning, a convolutional neural network (CNN, or Conv-Net) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics. They have applications in image and video recognition, recommender systems, image classification, medical image analysis, natural language processing, and financial time series. The study aims to automatically extract the self-learned features using an end-to-end learning CNN and compares the results with the conventional state-of-art and traditional computer-aided diagnosis system's performance. For the input layer, lung nodule CT images are acquired from the Lung Image Database Consortium public repository having 1018 cases. Images are pre-processed to uniquely segment the nodule region of interest (NROI) in correspondence to four radiologists' annotations and markings describing the coordinates and ground-truth values.

Architecture -



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1. ROI-based feature learning for efficient true positive prediction using convolutional neural network for lung cancer diagnosis.

Supriya Suresh1 • Subaji Mohan2

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2. Deep learning for lung Cancer detection and classification

A. Asuntha1 & Andy Srinivasan2

Received: 24 December 2018 / Revised: 8 October 2019 / Accepted: 13 October 2019 Published online: 02January 2020

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https://sci-hub.tw/downloads-ii/2020-01-03/dc/10.1007@s11042-019-08394-3.pdf#view=FitH

3. Journal Pre-proof

An effective approach for CT lung segmentation using mask region-based convolutional neural networks

Qinhua Hu, Lu´ıs Fabr´ıcio de F. Souza, Gabriel Bandeira Holanda, Shara S.A. Alves, Francisco Hercules dos S. Silva, Tao Han, Pedro P. Rebouc¸as Filho

Received Date: 14 July 2019 Revised Date: 6 December 2019 Accepted Date: 2 January 2020

https://sci-hub.tw/downloads-ii/2020-01-10/69/10.1016@j.artmed.2020.101792.pdf#view=FitH

4. Article Using2DCNNwithTaguchiParametricOptimization for Lung Cancer Recognition from CT Images

Cheng-Jian Lin * , Shiou-Yun Jeng and Mei-Kuei Chen

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https://www.researchgate.net/publication/340567244_Using_2D_CNN_with_Taguchi_Parametric_Optimization_for_Lung_Cancer_Recognition_from_CT_Images