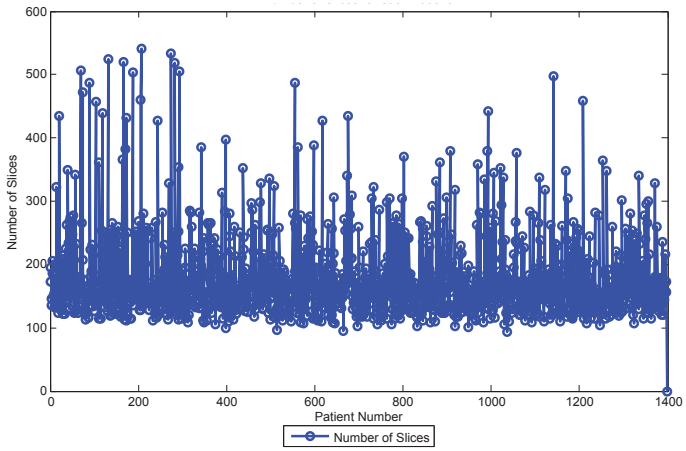

Figure 9: Number of Slices Per Patient in Data Science Bowl Dataset

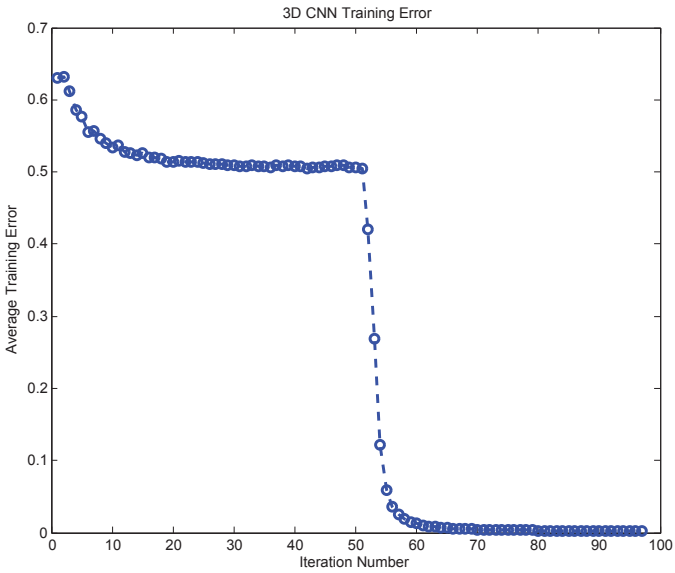

Figure 10: Average Training Error in 3D CNN

Initially speaking, the nodules in DSB dataset are detected and segmented using thresholding and U-Net Convolutional Neural Network. The diameters of the nodules range from 3 to 30 mm. Each slice has 512×512 pixels and 4096 gray level values in Hounsfield Unit (HU), which is a measure of radiodensity.

In the screening setting, one of the most difficult decisions is whether CT or another investigation is needed before the next annual low-dose CT study. Current clinical guidelines are complex and vary according to the size and appearance of the nodule. The majority of nodules were solid in appearance. For pulmonary nodule detection using CT imaging, CNNs have recently been used as a feature extractor within a larger CAD system.

For simplicity in training and testing we selected the ratings of a single radiologist. All experiments were done using 50% training set, 20% validation set and 30% testing set. To evaluate the results we considered a variety of testing metrics. The accuracy metric is the used metric in our evaluations. In our first set of experiments we considered a range of CNN architectures for the binary classification task. Early experimentation suggested that the number of filters and neurons per layer were less significant than the number of layers. Thus, to simplify analysis the first convolutional layer used 7 filters with size $5 \times 5 \times 5$, the second convolutional layer used 17 filters with $5 \times 5 \times 3$ and all fully connected layers used 256 neurons. These were found to generally perform well and we considered the impact of one or two convolutional layers followed by one or two fully connected layers. The networks were trained as described above and the results of these experiments can be found in Table 1. Our results suggest that two convolutional layers followed by a single hidden layer is one of the optimal network architecture for this dataset. The average error for training is described in Figure 10.

Another important parameter in the training of neural networks is the number of observations that are sampled at each iteration, the size of the so-called minibatch. The use of minibatches is often driven in part by computational considerations but can impact the ability of SGD to find a good solution. Indeed, we found that choosing the proper minibatch size was critical for learning to be effective. We tried minibatches of size 1, 10, 50 and 100. While the nature of SGD suggests that larger batch sizes should produce better gradient estimates and therefor work better, our results here show that the opposite is true. Smaller batch sizes, even as small as 1, produce the best results. We suspect that the added noise of smaller batch sizes allows SGD to better escape poor local optima and thus perform better overall.

The recognition results are shown by confusion matrix achieved on the DSB dataset with 3D CNN as shown in Table IV. As shown from the Table IV, Accuracy of model is 86.6%, Mis-classification rate is 13.4%, False positive rate is 11.9%, and False Negative is 14.7%. Almost all patients are classified correctly. Additionally, there is an enhancement on accuracy due to efficient U-Net architecture and segmentation.

Table IV: Confusion Matrix of 3D CNN using 30% Testing

	Predicted	
	Abnormal	Normal
Actual		
Abnormal	**0.853**	0.147
Normal	0.119	**0.881**

VIII. Conclusion

In this paper we developed a deep convolutional neural network (CNN) architecture to detect nodules in patients of lung cancer and detect the interest points using U-Net architecture. This step is a preprocessing step for 3D CNN. The deep 3D CNN models performed the best on the test set. While we achieve state-of-the-art performance AUC of 0.83, we perform well considering that we use less labeled data than most state-of-the-art CAD systems. As an interesting observation, the first layer is a preprcessing layer for segmentation using different techniques. Threshold, Watershed, and U-Net are used to identify the nodules of patients.

The network can be trained end-to-end from raw image patches. Its main requirement is the availability of training database, but otherwise no assumptions are made about the objects of interest or underlying image modality.

In the future, it could be possible to extend our current model to not only determine whether or not the patient has cancer, but also determine the exact location of the cancerous nodules. The most immediate future work is to use Watershed segmentation as the initial lung segmentation. Other opportunities for improvement include making the network deeper, and more extensive hyper parameter tuning. Also, we saved our model parameters at best accuracy, but perhaps we could have saved at other metrics, such as F1. Other future work include extending our models to 3D images for other cancers. The advantage of not requiring too much labeled data specific to our cancer is it could make it generalizable to other cancers.

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