LUNG CANCER DETECTION ON CT-SCAN IMAGES USING DEEP LEARNING

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ABSTRACT

The diagnose lung cancer from Computed Tomography (CT) images, segmentation is a crucial, yet challenging task. This is due to the several factors related to shape irregularity, tissue inhomogeneity, and low contrast between the lung inner tissues and the surrounding tissues. Existing image segmentation techniques rely on several parameters like image quality, tissue structure, and acquisition protocol to segment the different objects in the lung's CT-Scan image. However, existing segmentation techniques depend on user input and expert evaluation to manually initialize the segmentation, which is time consuming, labour intensive, prone to error, and not practical and adversely affects the accuracy and efficiency of such approaches. For this end, this research proposed the deep belief auto encoder model, a fully automated lung cancer detection solution. The model is composed of two components, the Deep Autoencoder (DA) and the Deep Belief Network (DBN). The DA extracts extract the discriminative features for the different objects in CT-Scan images. These features are then used to build the DBN network whose purpose is to determine the boundaries of the different objects, which facilitates image segmentation. The experimental evaluation shows that the proposed model with fully-automated segmentation outperformed the existing solutions that rely on the manual and semi-automated approach. Therefore, it is expected that incorporating the proposed segmentation method into the Computer Aided Design (CAD) systems will increase the accuracy of False-Positive Rate (FPR) by 0.035, Recall by 0.98102, F1 by 0.983001, Precision by 0.971 and diagnosis accuracy by 0.973 these systems for diagnosing lung cancer detection.

Keyword: Lung cancer detection, Deep autoencoder, computer aided design, classification and segmentation

1. INTRODUCTION:

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Among different cancer types, lung cancer is the second reason for cancer-connected transience between either genders (Hossain, Ahmed, & Kabir, 2014); (Khazaei et. al. 2017). In order for patient to survive, the cancer should be identified at the early stages. There are three different stages that the lung cancer goes through, where the stage one is the early stage, while the stage four is a terminal stage. The early identification and accurate diagnosis of lung cancer play an imperative role to successfully cure the tumor and save many lives (Ait Skourt, El Hassani, & Majda, 2018). Therefore, lung cancer detection using medical images like Computed Tomography (CT-Scan) and Magnetic Resonance Imaging (MRI) attracted a lot of efforts in both practice and research. However, the accurate identification of tumor in the image is challenging due to several reasons like low contrast, noise and shape irregularity. Computed Tomography (CT) scan is a popular technology used for diagnosing several diseases as it produces multi-dimensional images for human soft tissues and inner organs with high accuracy. It utilizes the fusion of several X-ray images captured via various angles to generate cross-sectional identities of definite regions in the examined item, which makes it easy to vision the object interior minus clipping (Ait Skourt, El Hassani, & Majda, 2018). The CT images are normally analyzed by a human expert, most probably radiologist (Bhatia, Sinha, & Goel, 2019). However, the manual analysis of CT images is a tedious and error-prone process (Song, Zhao, Luo, & Dou, 2017). Based on image processing, several computer-aided solutions have been proposed to automate the image analysis for the purpose of a cancer diagnosis. Such analysis normally starts by locating the boundaries of each object (region) in the image, based on which the different regions are isolated. Image segmentation is applicable in different executions such as robot vision, object recognition, and medical imaging (Pham, Siarry, & Oulhadj, 2018). CT imaging is commonly used to obtain high contrast images for the human lungs. Several imaging technologies like CT-Scan, and Magnetic Resonance (MR) and Positron Emission Tomography (PET), are used by Computer Aided Diagnosis (CAD) solutions to identify the tumor existence, position, and characteristics. Most of these solutions rely on the audiologist/physician expert to initialize and delineate the Region of Interest (ROI) surrounding the tumor (Kim, Lee, Lim, & Kim, 2018). The CAD then start identifying the tumor mass in the ROI. The human expert can supervise, identify and correct the errors that could occur during this process. Human intervention is necessary to prevent either over-segmentation or under-segmentation. Although semi-automatic tools can speed up the analysis process and decrease human error, the manual selection of the ROI is needed portion by portion that takes more time and probable to error. This study helps speeding up lung cancer diagnosis process by eliminating the need for human expert intervention in the segmentation phase of lung's CT-Scan images. The objective of this study is to investigate the problem of CT scan image mass segmentation and machine learning technique for lung cancer detect. To propose a Deep Belief Auto encoder (DBA) model by integrating the Deep Belief

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Networks (DBN) and Deep Auto Encoder (DAE) cancer mass boundary delineation that can improve lung image segmentation and automatically recognize lung cancer from CT scan identities and evaluate the accuracy of the initiated model and compare the improvement with existing solutions.

2. LITERATURE REVIEW:

Possible approaches currently used by some research community and found out that two lung regions extraction approaches, rule-based and pixel classification based are employed. In the rule-based procedure, a set of directives are employed in extracting the features. (Ginneken et al., 2001) found that greatest of the suggested procedures fall within this categorization. In addition, thresholding, region growing, edge detection, ridge diagnosis, morphological activities, and dynamic programming are few of the procedures utilized. Pixel classification is a different procedure utilized in the lung regions separation procedure, entailing every pixel in the CT image being grouped into an anatomical set. Such grouping entails different types of machine learning algorithms like neural networks and Markov random field. These classifiers are normally trained with the employment of a variety of local attributes inclusive of intensity, location, and texture estimates.

". Table 1, up to Table 3, Provides a summary of previous work related to the present study according to year.

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Table .1 State-of-arts related studies in 2018

Authors	Dataset	Accuracy (%)	FP/scan	Specificity (%)	Size (mm)	No. of nodules	Seep of respond time	Types of Nodules
Zhang et al. 2018	LIDC-IDRI	89.3	2.1	NI	NI	168	4.3min/case	Solitary, juxta-pleural and juxta-vascular nodules
Li et al. 2018	JSRT	94 84	5.0 2.0	NI	5–60	NI	NI	NI
Naqi et al. 2018	LIDC-IDRI	98.6	3.4	98.2	3–30	567	NI	Juxta-pleural and juxta-vascular nodules
Silva et al. 2018	LIDC-IDRI	92.20	NI	98.64	NI	219522 slices	NI	NI
Saien et al. 2018	LIDC LIDC-IDRI	83.98	3.9	90.70	3–30	198	NI	Isolated- juxta vascular-juxta-pleural and GGO nodules

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Table .2 State-of-arts related studies in 2017

Author	Dataset	Accuracy (%)	FP/scan	Specificity (%)	Size (mm)	No. of nodules	Seep of respond time	Types of Nodules
Farhangi et al.2017	LIDC-IDRI	NI	0.3 ± 0.5	NI	≥ 3	542	7.3s/iteration	Well circumscribed, juxta-vascular, juxta-pleural and pleural tail nodules
Wang et al. 2017	LIDC Private	92.75 ±12.83 83.19 ±15.22	NI	NI	2.03–38.12 1.64–58.94	893 74	6.92s/nodule	Isolated-juxta-pleural-cavitary- calcific and GGO nodules
Aoc et al. 2017	LIDC-IDRI	91.99	NI	96.48	3–30	6229	NI	NI
Shaukat et al.2017	LIDC-IDRI	98.15	2.19	96.01	3–30	2242	NI	NI
Liu et al.2017	LIDC	92.4	4.5	94.8	NI	978	NI	Well circumscribed-vascularized-juxta_pleural and pleural tail nodules
Qi et al.	LUNA16	90.7	4	NI	≥3	1186	NI	NI

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Table .3 State-of-arts related studies in 2016, 2015

Authors	Dataset	Accuracy (%)	FP/scan	Specificity (%)	Size (mm)	No. of nodules	Seep of respond time	Types of Nodules
Dhara et al.2016	LIDC-IDRI	89.73 82.89 76.14	NI	86.36 80.73 74.91	3–30	891	NI	Solid- part solid and non-solid nodules
Firmino et al.2016	LIDC-IDRI	94.4	7.04	NI	3–30	1109	12min/case	Isolated- juxta-pleural- juxta-vascular and GGO nodules
Setio et al.2016	LIDC-IDRI ANODE09 DLCST	85.4 90.1	1 4	NI	3–30	1186	1s/scan	Solid, subsolid, and large solid nodules
Froz et al.2016	LIDC-IDRI	91.86	NI	94.78	3–30	6415	NI	NI
Javaid et al.2016	LIDC	91.65	3.19	96.76	2.9–27	133	3.8s/slice	Solid, juxta-vascular, juxta-pleural nodules
Wang et al.2015	LIDC Private	88	4		3–30	127	NI	Juxta-pleural, juxta-vascular ,ground glass, opacity and solitary nodules
Akram et al.2015	LIDC	96.31	NI	96.77	3–30	NI	NI	Juxta pleura
Gong et al.2015	LIDC ANODE09	90.24 84.1	4.54 5.59	NI	2.87–30.89	302 39	NI	NI
Lu et al.2015	LIDC	87 85.2	2.61 3.13	NI	3–30	631	NI	Peripheral- chest wall and mediastinum nodules

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3. RESEARCH METHODOLOGY:

The research entails three stages with every stage's outcome being utilized as input for the succeeding stage. Figure 1 exhibits a recap of the research framework. In Phase 1, a literature review is conducted for the purpose of identifying the research problem and gaps, which achieves the first objective of this study. The outcome of this phase is the research problem and gaps that will be addressed in the subsequent phases. Based on the identified problem and gaps. Phase 2 implements the second objective which addresses cancer mass segmentation errors caused by the manual delineation, when carried out by human, by proposing the Deep Belief Autoencoder, which integrates the Deep Autoencoder with Deep Belief Networks for automatically segmenting the different objects in lung CT-Scan images. The outcome of this phase is the segmented images with clear and accurate identification of the tumor mass which helps the CAD system and/or radiologists to diagnose the tumors accurately. The accuracy of the proposed Deep Belief Autoencoder (ABA) segmentation representation is examined on using the dataset of "lung cancer" CT-Scan identities. The improvement of the automatic procedure introduced by the proposed the DBA is evaluated by the comparison with the conventional semi-automated methods.

Then carry out the experimental evaluation, this study will use a popular dataset called The Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI). This dataset is widely used by the extant research for lung cancer detection tasks (Armato III, McLennan et al. 2011). The LIDC-IDRI is a publicly available dataset for the medical imaging research community. the dataset was created by both the National Cancer Institute (NCI), the National Institutes of Health Foundation (FNIH), and the Food and Drug Administration (FDA), which initiated. Moreover, a cooperation between seven academic centres and eight medical imaging corporations was established to confront the organizational, technical, and clinical challenges, which resulted in comprehensive and robust database. The LIDC/IDRI Database consists of 1018 cases with every case entailing identities from a clinical thoracic CT scan and a correlated XML file that captures the outcomes of a two-phase identity annotation procedure discharged by four experienced radiologists. In the commencing blinded-read phase, every individual radiologist evaluated every CT-scan and marked lesions affiliated to one among the three groupings ("nodule > or =3 mm," "nodule <3 mm," and "non-nodule > or =3 mm"). In the succeeding unblinded-read stage, every radiologist separately evaluated their individual marks along with the anonymized marks of the three other radiologists to render an ultimate viewpoint. The objective of this procedure was to establish all lung tubercle in every CT scan minus the need for imposed agreement.

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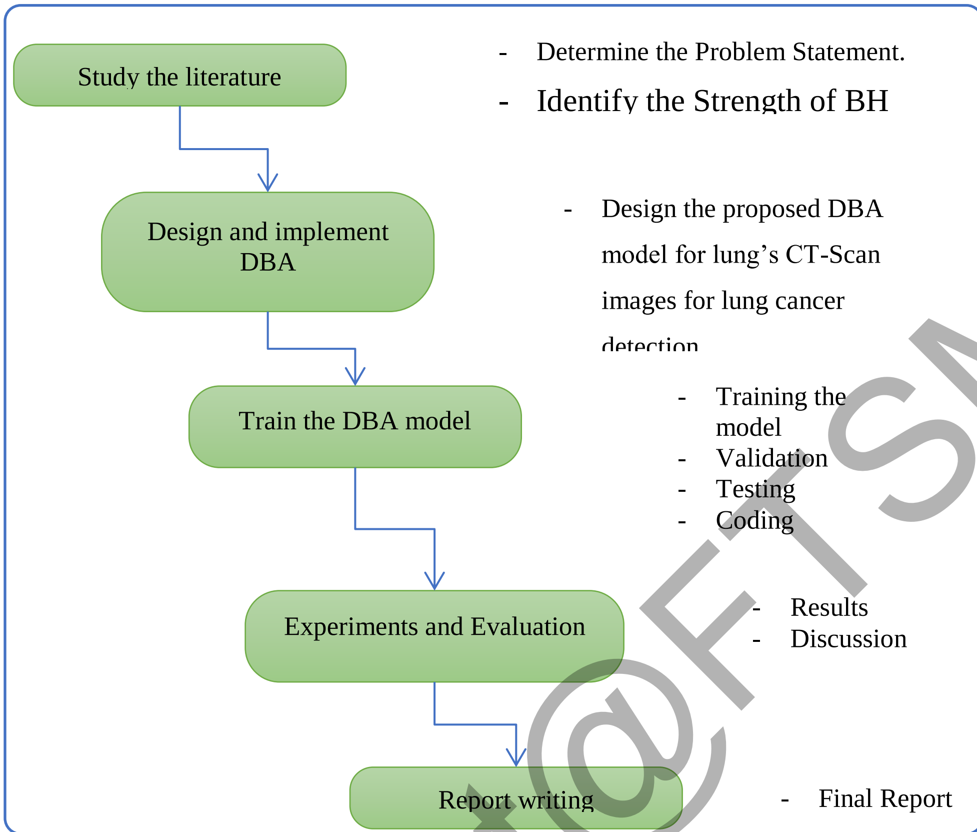

Figure.1 The general research framework

To execute the suggested DBA CT-Scan images, two levels are presumed, specifically offline training and online execution. In the training level, the lung CT-Scan images in dataset encountered various pre-processing procedures for instance smoothing, normalization, and noise extraction. Several filters have been applied on the images like median filter that replaces pixel value with adjacent pixel mean value. Additionally, Gaussian blur filter will be used for noise removal. For highlighting object boundaries in the image, Laplacian filter will be used so the edges of each region will be easily identified, which facilitates the detection of tumor mass in lung CT-Scan identities. The outcome of the said phase is the processed images to be used as an input for the next phase, in which the proposed DBA will be used for image segmentation.

The processed images coming from the pre-processing phase will be used by the proposed DBA, where the different objects in the CT-Scan image will be isolated. The proposed DBA is composed of two modules, the Deep Autoencoder (DA), that will be used for feature extraction, and DBN module for objects boundary delineation and image segmentation. As mentioned previously, the implementation of DBA will take place in two stages, training and testing. In the training phase of the proposed DBA model, the Deep Autoencoder will be used to extract the representative features of the different objects in CT-

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Scan images. Then these features will be used for the DBN module whose purpose then is to detect the boundaries of each object in the image as well as image segmentation. The segmented image will then be sent as an input for the Computer Aided Diagnosis (CAD) system, which will be used for identifying whether a suspected object is a tumor mass. The aftermath of this level is the diminished data estimates replacing the actual details at the discernment level.

On the other hand, at testing (online) lung cancer detection phase. To eliminate noise and image smoothness, the latest CT-Scan must undergo the same pre-processing as the training phase. The filters used at the training phase will also be used at the online operation of lung cancer detection using the proposed model. Likewise, the image will be sent to the DBA model, where the discriminative features will be extracted by the DA module and then used by DBN module to isolate the different objects in the image. The DBA will distinguish the objects of the CT-Scan using the patterns, parameters and latent characteristics in the hidden layers that have been learnt during the training phase. The segmented images will then be passed to the CAD system to identify the tumor mass. The outcome of this objective is the accurate Deep Belief Autoencoder (DBA) detection model that will be utilized as an input for the subsequent image execution procedures carried out by the CAD arrangement for confirmation of the lung cancer in CT-Scan identities. The depiction and implementation of this model were Figure .2 shows an overall structure of the suggested representation.

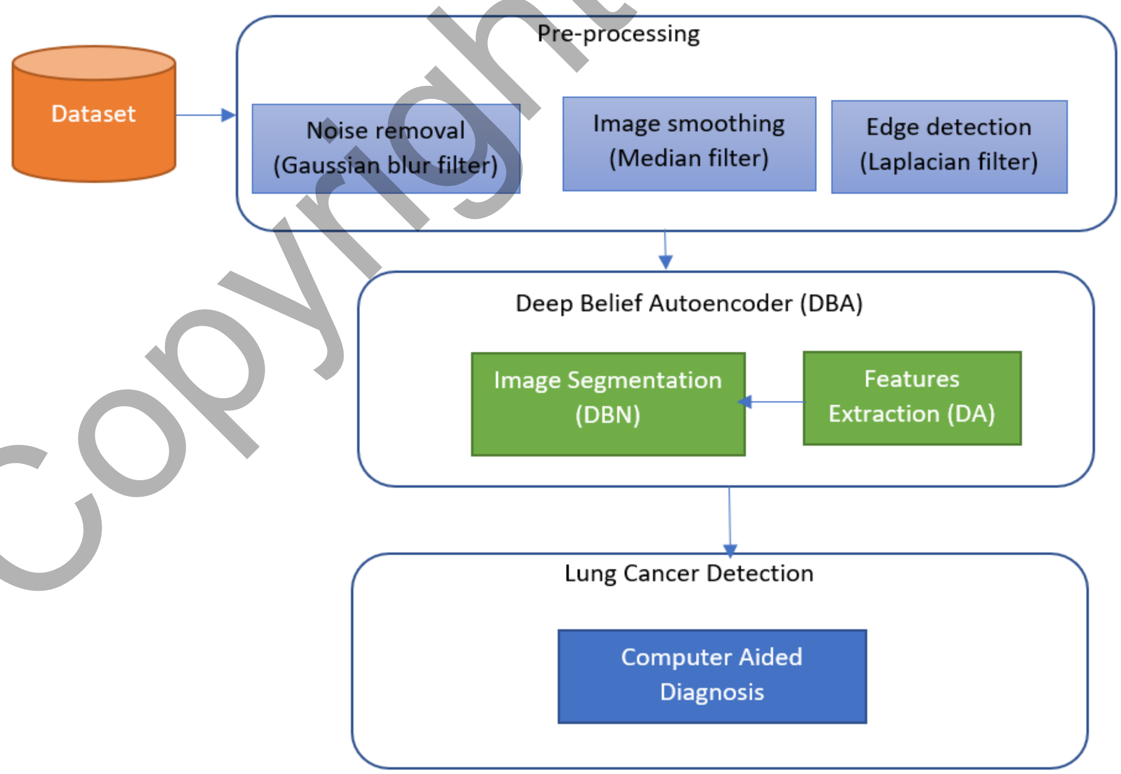

Figure .2 The General Design of the proposed model

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4. RESULTS DISCUSSION AND ANALYSIS:

The results in Table 4 show the accuracy, precision, recall, F1, and FPR of the proposed DBA model. As can be noticed, the precision is enhanced with the increase in size of hidden thickness in DA, DBN and CNN. This is attributed to the ability of the higher order features perceive the characteristics of the tumor mass representation more accurately. It also can be seen that the accuracy starts to fluctuate when number of hidden layers becomes higher than 7. The reason is that when we add more layers to the model, the complexity increases, which will have a negative effect on the performance of the model. This is attributed to the number of features generated. That is higher number of hidden layers means generating more features, and when the number of these features increase, the risk that model get overfitted increase, which leads to decrease in the detection accuracy, precision, recall and F1. The overfitting will also increase the False Positive Rat (FPR) which decreases the detection performance of the proposed DBA model.

Table 4. The detection accuracy, precision, recall, F1 and FPR of the proposed DBA model

# of Hidden Layers	Accuracy	Precision	Recall	F1	FPR
1	0.821	0.841	0.85102	0.831001	0.274
2	0.843	0.86	0.87002	0.853001	0.236
3	0.886	0.902	0.91202	0.896001	0.177
4	0.904	0.92	0.93002	0.914001	0.112
5	0.932	0.994	1.00402	0.942001	0.093
6	0.941	0.963	0.97302	0.951001	0.078
7	0.96	0.97	0.98002	0.970001	0.063
8	0.973	0.977	0.98702	0.983001	0.048
9	0.971	0.975	0.98502	0.981001	0.044
10	0.98	0.97	0.98002	0.990001	0.039
11	0.978	0.972	0.98202	0.988001	0.038
12	0.973	0.971	0.98102	0.983001	0.035

5. CONCLUSION:

The problems of MRI of the lung are represented by the low density in some protons in the lung and signal manipulation due to reactivity to air-tissue interfaces. Besides, the nature of lung imaging in MRI relies on the victim 'ability to undertake the breath holding directives in comparison to CT imaging. Although MRI technology has shown its worthiness for lung imaging technique, has several challenges related to robustness and cost effectiveness. This research proposed and built a deep belief autoencoder

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model as a fully automated lung cancer detection solution. The model incorporates deep learning for image delineation in order to improved image segmentation. Two components constitute the proposed method, the Deep Autoencoder (DA) and the Deep Belief Network (DBN). The purpose of DA is to extraction extract the features of the different objects in CT-Scan images. These features are then used to build the DBN network whose purpose is to determine the boundaries of the different objects, which facilitates image segmentation. Building the Deep Autoencoder (DA) for features selection take place in two stages, training and testing.

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