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Supervised Classification of Lung CT Images using Deep Learning Algorithm

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Abstract: Deep learning has accelerated the technological evolution of the current era to a greater extent. Conventional classification systems rely on laborious feature engineering process which requires expertise in domain knowledge for data interpretation. In contrary, deep learning without using a domain expert can extract distinct features from the data. In this study, we conduct some preliminary experiments using the deep learning approach to classify diseased human lung CT images from normal by using a feature set. A method based on the extraction of image features for training the algorithm and the comparison of these features for final classification using Support Vector Machines (SVM) is proposed. The input images are thresholded using otsu's method followed by region-based segmentation to obtain Region of Interest (ROI). A feature set is formed using features extracted from the ROI and the same is trained to the classifier to get the intended output. Implementation of the classifier was brought about using Anaconda 2019 (Python 3.7) version. Accuracy of the proposed algorithm was found to be around 0.95 (95%). The classifier algorithm can be further implemented on a hardware platform for investigation of diseases with automatic decision-making.
Keywords: Deep learning, classification, image processing, supervisory learning, python, CT image, SVM

I. INTRODUCTION

Artificial intelligence is a field that displays human intelligence in a machine, machine learning and deep learning are the domains which work under AI. Machine learning allows computers to learn without explicit programming, whereas deep learning a type of machine learning enables system to read a data and comprehend it. These methods enable computers to extract patterns corresponding to a specific data set and automatically reason them [1,2](Goodfellow et al., 2016; Robert 2014). Machine learning categories include supervised, semi-supervised, unsupervised, active learning and reinforcement algorithms. Deep learning methods are advanced phase of these algorithms which using a neural network classifies a data and allows automatic decision-making [3](Norris 2017).

Medical imaging owing to its impact in early diagnosis and treatment of diseases is a rapidly growing research area. Image processing in medical imaging is as relatively significant. Image processing concepts include image classification, object detection, pattern recognition, reasoning etc. These concepts allow extraction of valuable patterns from a specific data with increased accuracy. Machine and deep learning methods aid in classification and automatic decision-making for multi-dimensional medical data [4](Mahesh 2011). Specific diseases can be studied effectively in medical imaging using machine learning algorithms. A simple mathematical solution or model cannot accurately distinguish lesions and organs in medical image processing. Machine learning employs pixel-based investigation of medical images [5](Suzuki 2012).

Supervised learning approach provides a computer system with a training set with suitable objectives, which gives accurate response for the inputs given. Classification and regression are two categories of supervised learning. A classification method distributes the inputs into various classes, the trained system allots hidden inputs to these classes. This process is called multi labeling process. In regression technique continuous outcomes are obtained. Predictions are evaluated using root mean squared error (RMSE) for regression and as performance measure of accuracy in classification [6](Jankowski and Grochowski 2004).

CT scan imaging uses X-rays to obtain structural and functional information about various organs of the human body. CT image is X-ray absorption profile based reconstructed image. Based on the fact that different tissues and matter absorbs X-rays differently, X-rays are used in diagnosis. Bones appear white, while soft tissues appear gray in a CT image. Cavities of lungs filled with air appear black. CT performs as a supplement to Magnetic resonance imaging and ultrasonography in diagnosis. They are particularly used in imaging and diagnosis of brain, liver, chest, abdomen, pelvis and spine.

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II. LITERATURE REVIEW

Many research groups have reviewed and have reported about the emerging trends of deep learning applications in medical image processing [7,8](Latif et al., 2019; Maiers et al., 2019). The computational implementation difficulty of convolutional neural networks owing to high memory bandwidth requirement and intensive computation resources have paved way for the use of deep learning algorithms. Hailesellasie et al., 2018 [9] proposed a deep CNN (SqueezeNet) for image classification that enables significant reduction in the networks' model size and improves the accuracy and performance. Lin et al., 2016 [10] and Papandreou et al., 2015 [11] have proposed weakly supervised learning, in which labeled training data is improvised with image annotations and scribbles. Semi-supervised learning method to train the network for cardiac MR image segmentation was reported by Bai et al., 2017 [12]. They were able to effectively improve segmentation accuracy. Nakata 2019 [13] in their review has elaborated on the general image data sets for supervised learning. Ahmed et al., 2019 [14] in their article has proposed a supervised learning approach for classification of lung cancer CT-scan images. They have combined classical feature-based SVM classifier and supervised learning algorithm for the accurate classification and detection of lung nodules for early and efficient diagnosis of lung cancer. Jog et al., 2014 [15] proposed a regression supervised learning algorithm for improving the resolution of a brain MR image. Tu et al., 2007 [16] has reported a supervised learning approach for automated extraction of the major cortical sulci from MR images.

III. METHODOLOGY

Various steps are performed on the input medical images before the detection of output as elaborated in figure 1. Initially, the medical images are given as input to the machine and deep learning algorithms and pre-processed for the removal of distortion and noise. After that, the images are divided into different segments to zoom the interested area (ROI). Then, the features are extracted from these segments through information retrieval techniques. The desired features are selected and the noise is removed. After the process of feature extraction, a database is created based on the feature parameters. There are two processes involved before the final classification; they are the training phase and test phase. During the training phase, the network is pre-trained by giving 80% of the input data (training data) using supervised learning method. In the test phase, the remaining untrained images (test inputs) are given as input to the classifier, where the test input features are compared with the pre-trained image registry in the database. Finally, the classifier is used to classify the extracted data and make predictions based on this classification. These steps are used in every experiment of machine learning.

Python was chosen as the development platform due to its vast set of APIs and modules. The syntax was very easy to code and implement hence coding these algorithms using python helped creating logic. Human Lung CT scan images were given as inputs to the deep learning algorithm, which has been developed in python language.

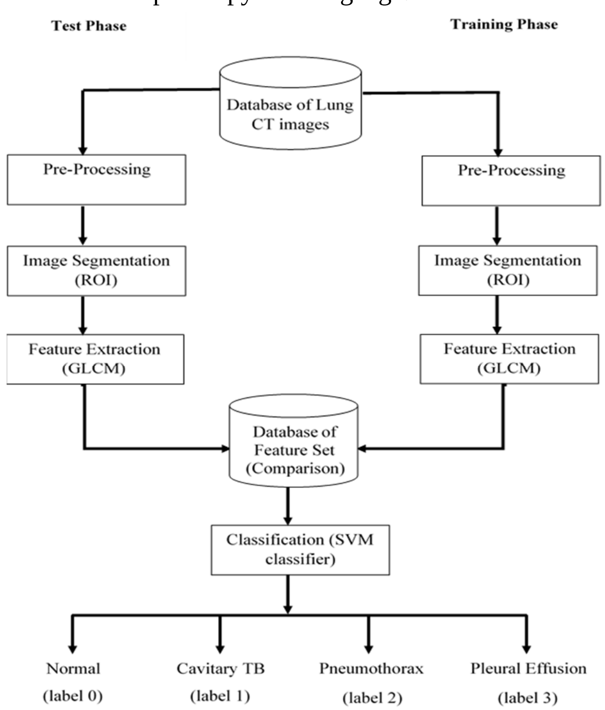

Fig. 1 Block diagram of the proposed system

A. Thresholding

The input images are pre-processed using the method of thresholding. The process of converting grey scale images to binary images is called thresholding. The input image is thresholded using Otsu's method. Otsu's method thresholds the input by minimizing the within-class variance of two different pixel groups.

The pixels are further characterized as black and white areas based on the variance and mean value to get a monochromatic image. In the watershed method, gradient of the image is considered as a topographic surface. Pixels with more gradient are shown as continuous boundaries.

A black and white monochromatic image is obtained as output of the Otsu's thresholding and a segmented output image is obtained from watershed segmentation method.

The features extracted using this algorithm are Region value r, Axis factor of 2-D image X, Axis factor of 2-D image Y. Figure 2 (a) shows the normal lung CT image, which is the input. Fig 2 (b) shows the thresholded image of (a). Fig 2 (c)shows how many unique segments are found I the image in terms of the grey scale. Here 68 unique segments are found.

B. Segmentation

Image segmentation involves dividing an image into segments/Region of interests with similar features. Region based segmentation; a type of Local segmentation method is used for image segmentation in this project.

(a)

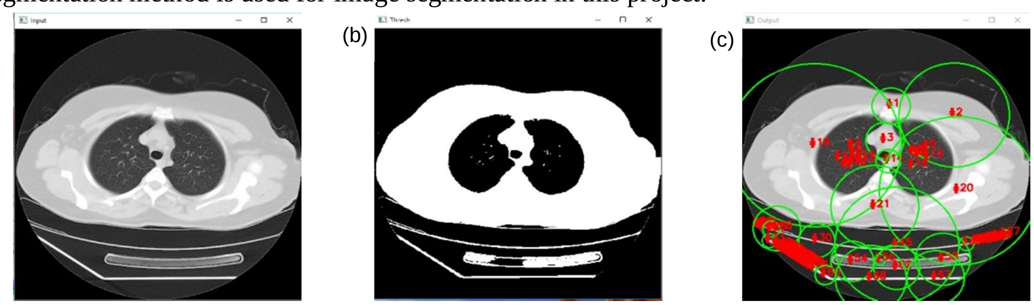

Figure 2 output of watershed algorithm (a) Normal human lung CT image input (b)Thresholded image of (a) using Otsu's method (c) image showing 68 unique segments in (a)

The edge-based segmentation method is employed, which is one of the structural techniques based on discontinuity detection. Edge information of an image is not provided by a single intensity value, hence rapid change of intensity value-based technique brings about the segmentation.

Two basic edge detection techniques namely sobel operator, canny operator is used to detect the edges. Segmented monochromatic image showing the required ROI is the output. The features extracted from this algorithm are marker_area and dist_transform.

Figure 3 (a) shows the lung CT image of the disease, Cavitary TB. Fig 3 (b)represents the thresholded image of (a) using sobel method. It shows the grain pattern of the monochromatic image and the deviation from the normal lung CT image. Fig 3 (c) shows the thresholded image of (a) using canny method. It shows the thermal patterns of the deviations i.e, cavities in the lung area. from the normal lung CT image. Fig 3 (d) represents the segmented ROI in the image (a) by using region segmentation method.

(a)

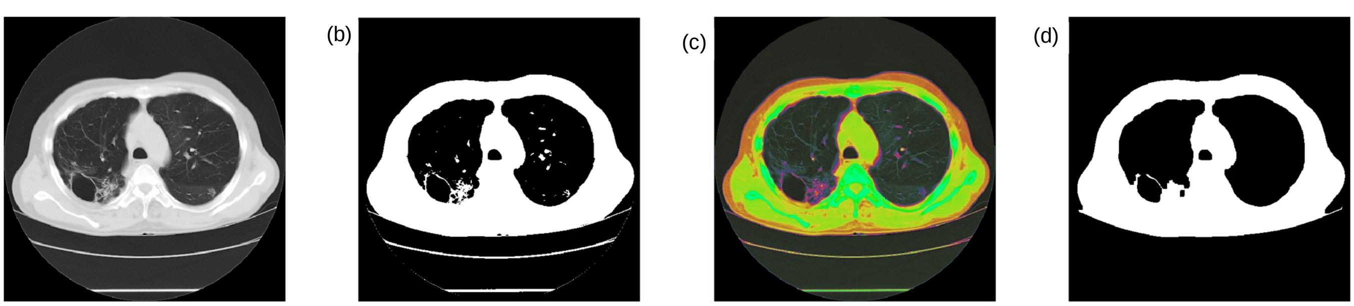

Fig. 3 output images of segmentation algorithm (a) input (b) & (c) thresholded images of (a) using sobel and canny operator respectively (d) segmented ROI of (a)

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C. Feature Extraction

For feature extraction Edge Detection technique was used, under which the Sobel operator method was implemented. Three algorithms were used to extract the desired features. They are grey co-occurrence matrix, segmentation, watershed.

Seven feature parameters are extracted, they are:

1) Correlating factor of grey level X_S
2) Correlating factor of grey level Y_S
3) Region value r
4) Axis factor for the 2-D image X
5) Axis factor for the 2-D image Y
6) Marker_area
7) Dist_transform

The input data images are labeled as 0,1,2,3 which represents the human lung CT images of Normal, Cavitary TB, Pneumothorax and Pleural effusion respectively. The feature set was formed using the register and retrieval method using an Excel datasheet. Process of transforming the data sets into one system i.e., database is called registration. A database or repository is necessary for comparison and integration for the varied data obtained in various aspects. A set of specific parameters are selected as standards which are used to calculate the similarity between two images using the developed algorithm.

Gray-level co-occurrence matrix (GLCM), is a statistical method that examines the spatial relationship of pixels. Texture of an image is characterized based on the calculation in a specified spatial relationship how often pairs of pixels with a specific value occurs. Creating a GLCM of order N x N, where N is the Number of levels, which specifies the number of grey levels between the minimum and maximum values, restricted to the range of 0 to 256, then extracting statistical measures from this matrix. Here N=4. The features extracted using this method are the correlating factors of grey level X_S and Y_S. Fig 4 represents the lung CT image of disease Pneumothorax and its texture scale in spatial axis. The output images show the dissimilarities and correlation.

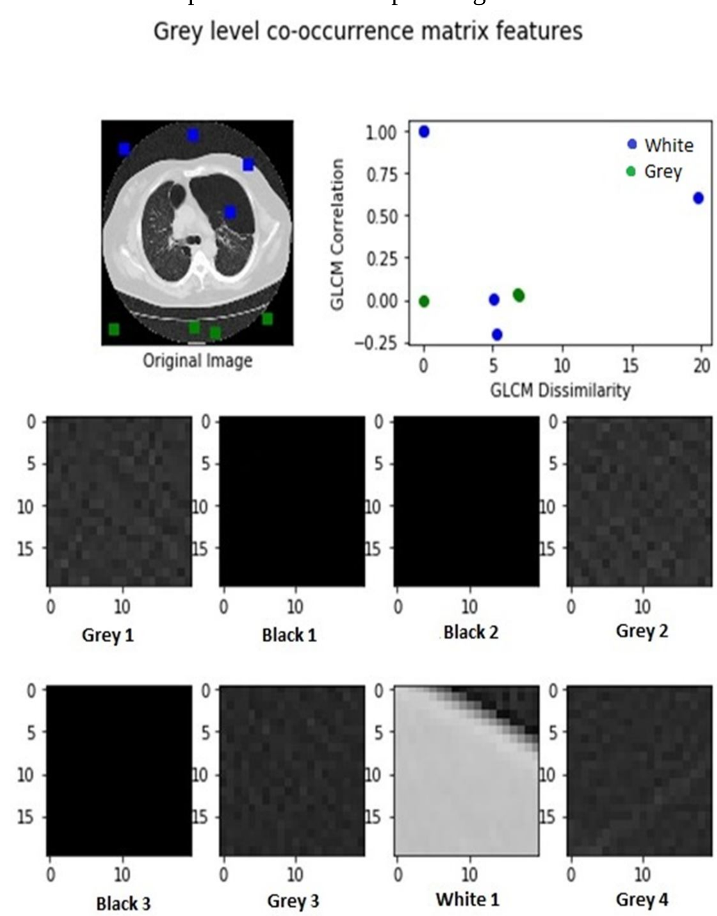


Figure 4 output of GLCM algorithm

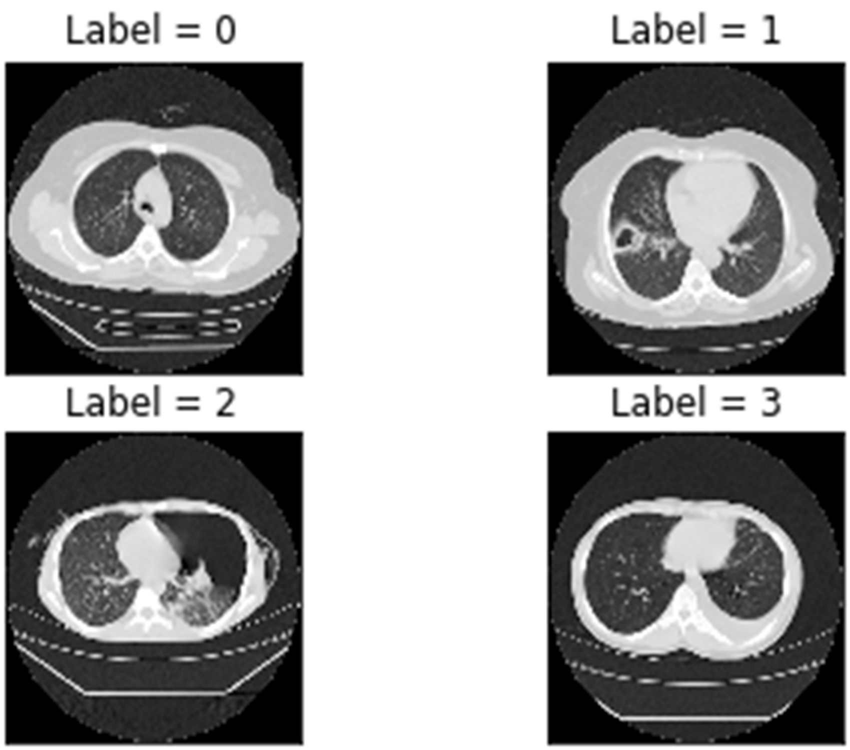
IV. RESULTS AND DISCUSSION

A. Classification

The feature extracted results of the training and test phases are compared with the help of the feature set formed. Based on the labeling the images are classified to their respective classes. Supervisory learning for classification and Supportive Vector Machines (SVM) as the classifier is employed. SVM discriminately classifies based on a separating hyperplane or a line. The algorithm outputs an optimal hyperplane, for categorizing the test data in comparison to the labeled training data. Support vectors, the points closest to the hyperplane are found and the distance between the line and these points are computed, called the margin. Hyperplane with maximum margin is the optimal hyperplane. Thus, SVM makes a decision boundary in a way that it separates the classes as wide as possible.

Figure 5 shows the classifier output based on the labels given during the training phase. Image of label=0 represents the normal lung CT image. Image with label=1 represents the lung CT image of disease Cavitary TB, which shows hole like cavities in the lung area. Image with label=2 represents the lung CT image of disease Pneumothorax, which shows trapped air in the upper part of the lung. Image with label=3 represents the lung CT image of disease Pleural Effusion, which shows the accumulation of body fluids in the lower region of the lungs.

Test inputs predicted with labels



Accuracy Score of SVM = 0.95

Figure 5 output of the classifier algorithm

V. CONCLUSIONS

A deep learning algorithm developed using Support Vector Machines model for classification of CT images of normal and diseased human lung. The developed algorithm was implemented in Anaconda 2019 (python 3.7) version and checked for its accuracy. The accuracy was found to be 0.95 i.e. around 95%. The developed algorithm can be implemented for similar image processing applications with its high accuracy. The code can be implemented on a hardware platform to obtain efficiency.

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REFERENCES

[1] L. Goodfellow, Y. Bengio, A. Courville and Y. Bengio, 'Deep learning (Vol. 1)', Cambridge, MIT Press, 2016.

[2] C. Robert, 'Machine learning, a probabilistic perspective', CHANCE, Vol. 27, No. 2, pp. 62-63, 2014.

[3] D. J. Norris, 'Machine Learning: Deep Learning', Beginning Artificial Intelligence with the Raspberry Pi, Springer, pp. 211-247, 2017.

[4] M. Mahesh, 'Fundamentals of medical imaging', Medical Physics, Vol. 38, No. 3, pp.1735-1735, 2011.

[5] K. Suzuki, 'Pixel-based machine learning in medical imaging', International Journal of Biomedical Imaging, vol. 2012, Article ID 792079, pp. 1-18, 2012.

[6] N. Jankowski and M. Grochowski, 'Comparison of instances seletion algorithms I.algorithms survey', 7th International conference on artificial intelligence and soft computing 2004, Zakopane, Poland, Springer, pp 598-603.

[7] J. Latif, C. Xiao, A. Imran and S. Tu, 'Medical Imaging using Machine Learning and Deep Learning Algorithms: A Review', IEEE- iCoMET 2019, Sukkur, Pakistan, 2019.

[8] A. Maier, C. Syben, T. Lasser and C. Riess, 'A gentle introduction to deep learning in medical image processing', Z Med Phys, Vol.29, No.2, pp.86–101, 2019.

[9] M. Hailesellasie, S. R. Hasan, F. Khalidt, F. Awwad and M. Shafiquet, 'FPGA-Based Convolutional Neural Network Architecture with Reduced Parameter Requirements', IEEE International Symposium on Circuits and Systems (ISCAS), Florence, Italy, 2018.

[10] D. Lin, J. Dai, J. Jia, K. He and J. Sun, 'ScribbleSup: scribble-supervised convolutional networks for semantic segmentation', In: CVPR, pp. 3159–3167, 2016.

[11] G. Papandreou, L. C. Chen, K. Murphy and A. L. Yuille, 'Weakly- and semi-supervised learning of a deep convolutional network for semantic image segmentation', In: ICCV, pp. 1742–1750, 2015.

[12] W. Bai, O. Oktay, M. Sinclair, H. Suzuki, M. Rajchl, G. Tarroni, B. Glocker, A. King, P. M. Matthews and D. Rueckert, 'Semi-supervised Learning for Network-Based Cardiac MR Image Segmentation', In: Descoteaux M. et al., (eds) Medical Image Computing and Computer-Assisted Intervention − MICCAI 2017, Vol 10434, Springer, Cham, pp. 253-260, 2017.

[13] N. Nakata, 'Recent technical development of artificial intelligence for diagnostic medical imaging', Japanese Journal of Radiology, Vol. 37, No. 2, pp.103-108, 2019.

[14] S. R. A. Ahmed, I. A. Barazanchi, A. Mhana and H. R. Abdulshaheed, 'Lung cancer classification using data mining and supervised learning algorithms on multi-dimensional data set', Periodicals of Engineering and Natural Sciences, Vol. 7, No. 2, pp.438-447, 2019.

[15] A. Jog, A. Carass and J. L. Prince, 'Improving Magnetic Resonance Resolution with Supervised Learning', IEEE 11th International Symposium on Biomedical Imaging (ISBI), Beijing, China, pp. 987-990, 2014.

[16] Z. Tu, S. Zheng, A. L. Yuille, A. L. Reiss, R. A. Dutton, A. D. Lee, A. M. Galaburda, I. Dinov, P. M. Thompson and A. W. Toga, 'Automated Extraction of the Cortical Sulci Based on a Supervised Learning Approach', IEEE Transactions on Medical Imaging, 26(4):541-552, 2007.