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Lung Cancer Nodule Detection by Using Selective Search Feature Extraction and Segmentation Approach of Deep Neural Network

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Abstract

The study addresses the implementation of the selective search for the classification of cancer nodules in the lungs. The search processes integrate the power of both segmentation as well as exhaustive search for detection of an object in an image. In addition, the features of the cancer stage classifier are also used for cluster organization from the histogram to set the difference between inter-class variance. The selective search makes use of class variance to trace out meta-similarities. Later the neural network is implemented for the cancer stage classification.

Disciplinary: Computer Science, Machine Learning, Deep Neural Network, Image Segmentation.

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1 Introduction

Image segmentation for cancer nodule detection is a vital branch of artificial intelligence for medical science. The generic algorithms aim for segmentation by unique partitioning the image. The research is specified to the lung cancer imaging for cancer cell identification and functional relation of its attributes to its specific stage. Appropriate localization through cancerous identification nodules by their characteristics is leading medical research. The same can be implemented in image classification and machine learning with cell attributes like shape, size, texture, etc. Some characteristics like texture and size vary widely from an infected cell to normal.

An exhaustive search to localize the cancerous nodule is a method to scan thoroughly to determine the Region of Interest (ROI). This algorithmic process has many drawbacks, such as time

complexity searching the entire scan image for the possible infected nodule and comparison with already occurring positive outcomes. It is computationally infeasible for the sliding window technique for searching brute forcibly using nodule size and shape. A required process is needed to do a sophisticated task to capture the highly guaranteed location. This kind of classification is the future of Artificial intelligence to generate the exact location for medical diagnosis. It helps the patient to determine and possibly eradicate the affected cell or to stop further spreading.

The applied method for the research is selective search. This method is based on hierarchical grouping. The combination is supported by the segmentation approach applied for the analysis. The greyscale scan images are chosen more than other color variants due to their availability. Therefore, all the generic research for segmentation with color-coding cannot apply to the study. Instead, the transitional pixel from cancerous to non-cancerous pixels can be depicted in grayscale as it varies widely in its range.

A series of generic algorithms have yielded tremendous approaches to recognizing the object in an image using the segmentation approach. Fan Zhang et al. classify lung nodules images by using the machine learning SVM approach for overlapping nodules [1]. Various Deep learning approaches were conducted for image classification for the detection of cancer nodules.

As Image segmentation approaches with the help of thresholding gives a better move towards object identification in an image [2,3,4]. Chaddad et al. [5] analyzed the texture of cancer for predicting the disease. Uijlings et al. [6] proposed the diversifying sampling method by implementing an exhaustive search for image segmentation. The efficient graph-based image segmentation approach is addressed by Felezenszwalb [7] for detecting the number of graph edges linearly very fast. It can preserve the smooth detail in a deficient variability object in an image, which is most important in the case of cancer nodule classification.

The collected dataset for the research is licensed under the cancer imaging Archive (TCIA) as NSCLC-Radiomics, created by Justin Kirby. This collection contains 52073 images of 422 non-small cell lung cancer patients. the data is sub-divided into three stages and their subcategories, respectively [8].

2 Methodology

The selective search method carried out for the research is implemented to detect the infectious cell by combining multiple diversifications. The basic idea behind the study is to find out the proper location and to study related results. The object location hypothesis is diversified by varying color space, by varying size, by varying the nodule's shape and position, and by weighing up the similarities among them. The combination of these above singular complementary strategies is capable of finding a better probable object location.

The histogram of many regions has shared similarities with the infected nodules. The boundaries of the infected cells and the chest rib scan in the image are sometimes may less clear as both share almost the same intensity value [3]. The condition of intensity may be affected by a change in contrast or brightness. The neighborhood Pixels with nearly the same intensity are

grouped to form superpixels in their respective level of the hierarchy. Finally, the nodule shapes or similar structures from each layer are captured and communicated for the final assessment.

2.1 Selective Search

The main idea behind the selective search is to form a superpixel from similar pixels. The superpixel is created by a cluster of the same intensity pixel. It happens in all the layers of the selective search structure. The selective search approach for the formation of superpixels is based on pixel attributes. The attributes like color, texture, size and shape similarities are combined to figure out the superpixel.

2.1.1 Colour

Computing 255 - histogram measures the greyscale channel of an image is classified by distance algorithm. The histogram of image pixels is divided into ten equal width bins. Pixels that fall into a specific range are colored in an identical color. Superpixel is formed later by matching its attribute structure.

2.1.2 Texture

The texture of the cancerous cell nodule has a vital role in the classification of the tumor stage. All the partial-rounded clusters cannot be tagged as infectious. The selective search can be able to extract different textures from an image. Infectious nodules' texture can be well-distinct in the training set, which can be later abled to classify the contagious cell. Gaussian derivative at eight orientations with a ten-bin histogram is used as a texture descriptor.

The formation of lung nodules has a different shape and size invite comparison with its regular spherical shape. However, research is reported that 80% of standard partial spherical shapes are non-cancerous. So the central idea of the study is to capture the proper texture.

One centroid selected nodule is chosen as a representative SIFT descriptor for applied nodules. A four-length descriptor vector projects a 128 length SIFT descriptor for classifying every slight possibility.

$$P_i = P\ (\ y = i \mid d).\qquad i = \text{Class} \tag{1},$$

$$V_{\text{nodule}} = (\ P_1, P_2, P_3 \ldots\ldots P_i) \tag{2}.$$

Similarities are calculated by cosine value between two selected nodules.

$$\text{Similarities}\ (\ \text{Nodule}_i\ ,\ \text{Nodule}_j) = \text{Cos}\ (\ V_i, V_j) \tag{3}.$$

A weighted similarity matrix is created to map similarities among nodules. Popular machine learning method SVM is applied later section to classify among them

2.1.3 Shape

The scale of the pyramid layer formed from the selective search is standardized in proportion to the stage of the cancer cell. All the probable nodules are being checked for compatibility with the

standardized nodules. Hence the phases of cancerous cells are decided by the scale and the layer of structure. The layer uniquely defines each scale on it. The unit of scale is considered as the size parameter for the nodule. In contrast, the shape of the cluster is recognized by the algorithm. Less the difference between forms is more the similarities between nodules.

The shape from the image extracted may not be fitted precisely into the standardized one. The regional proposal algorithm helps to detect the difference between the two collected samples.

2.1.4 Size

Another predominant feature is the size of the detected nodules. It helps to analyze the stage of the cancer cell. The part is well executed with the help of sliding kernel methods. The image multiscale plays a vital role in size representation. The underlying idea behind this execution is to extract the expected ROI from an object.

The original image is placed at the bottom of the multiscale representation. The min scale window collects the subsample from classifying the object at the bottom of the image. The large-scale window is used on the top of the structure to rank the most significant possible nodule size. The subsequent stages in the pyramid are the transactions in the layer image's size with respective sliding window sizes.

Let the original size of an image (X, Y)

Suppose the size of the sliding window (x, x)

$$\text{Size of the subsequent layer} = (X, Y) \times \frac{max - (min + \sum_{i=1}^{i} layer_i)}{max} \quad (4),$$

$$\text{Size of search window} = (x, x)_{min} + \sum_{i=1}^{i} layer_i \quad (5),$$

where $(x, x)_{min} = (1,1)$.

2.1.5 Position

The position of the nodule with some other features holds a strong probability for tracking the precise nodule. The position of viable infected cells is differed as per the stage and type of infection. This stand-alone feature has the scope to deduce the stage of the patient. The grid of the image multiscale can map the position of the infectious nodule.

The nodule is classified as mainly four categories, i.e., well-circumscribed, Juxtra-vascular, Juxtra-pleural, and pleural- tail. Centrally located nodule without morphed by any vascular tissue is known as well-circumscribed. If The same is connected to vascular tissue is called vascular. If the nodule is attached to the pleural wall, then the nodule is called Juxtra - pleural Likewise, only bound by the tail is called the pleural tail.

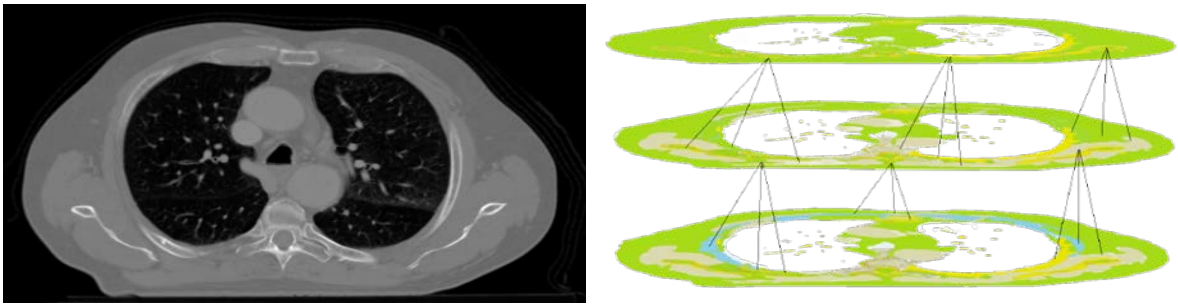

Figure 1: The raw image of a computed tomographic image of lung cancer before processing into selective search (left). The selective search alike pyramid structure layer-wise processing for classification of cancer nodule (right).

2.2 Clusterization

The cluster formation for the nodule and the background area depends on the meta-similarities among the pixel attributes. All the characteristics are related to the specific clusterization domain. A particular range of domains adopts the pixel refers to its details.

$$C(r_i, r_j) = \sum_{k=1}^{n} min\ (r_i^k, r_j^k) \quad (6).$$

The paper is restricted to 2D monochromatic CT images. The image f(n) is a two-dimensional discrete spatial coordinate system of n = (x, y). The non-zero image matrix contains the image domain $[0, X-1]$ * $[0, Y-1]$. The integer value of each pixel is quantized to f - level. Here f is the grey level values. It is plotted in the histogram or frequency of occurrence or H_f, ranging from 0 to XY. The optimal threshold for an image Th_{ot} for the range [0-255] is selected for an absolute range value so that the class separability (CS) has the maximum value. C_k is determined as the k-th cluster of gray levels then P(z) is termed as the probability of the existence of the pixel with gray level z.

$$P_k(T) = P_r(C_k) = \sum_{z=8k-8}^{8k-1} h(z) \quad (7),$$

$$m_k(T) = \sum_{z=8k-8}^{8k-1} z\, P_r\{z \mid C_k\} = \frac{1}{P_k} \sum_{z=8k-8}^{8k-1} z\, h(z) \quad (8),$$

$$\sigma^2 = \sum_{z=8k-8}^{8k-1} [z - m(T)]^2 h(z) \quad (9),$$

$$m(T) = [p_1 m_1(T) + p_2 m_2(T) \ldots . + p_{32} m_{32}(T)] \quad (10),$$

$$CS(T) = \frac{P_k(T) P_{k+1}(T) [m_k(T) - m_{k+1}(T)]^2}{\sigma^2} \quad (11),$$

where $k + 1 \leq 32$

$m(T)$ = the mean of grey level T and σ is the variance among class

The criterion function for class separability is the means between the classes. It can be implemented to separate among classes by keeping variance as low as possible.

The similar Pixel intensities limited by threshold are assigned to form a cluster, Thereby the dissimilarities are separated by the above criterion function to create another collection.

In the hierarchy, Two adjacent clusters are merged into a supercluster. The merger is based on the difference between the means value of two adjacency clusters and the resultant cluster variance. The probability density function measures these two factors.

The distance of the C_k and C_{k+1} cluster is defined as

$$Dist\ (C_k, C_{k+1}) = \sigma^2_{inter}\ (C_k \cup C_{k+1})\ \sigma^2_{intra}\ (C_k \cup C_{k+1}) \quad (12).$$

Inter-class variance is defined as a means of two neighbor clusters before forming a supercluster and their total mean value. Furthermore, Intraclass variance is the variance of merged supercluster pixel values. The resultant size of the supercluster is the addition of the two neighbor cluster.

$P(C_k)$ is the occurrence probability belonging to cluster C_k

$$P(C_k) = \sum_{T_{k-1}+8}^{T_k} \frac{h(z)}{N} \quad (13),$$

$h(z)$ = Pixel frequency occurrence with grey level z .

N = total number pixels in the image

$$Dist\ (C_{k_1}, C_{k_2}) = \sigma_1^2\ (C_{k_1} \cup C_{k_2})\ \sigma_A^2\ (C_{k_1} \cup C_{k_2}) \quad (14).$$

Inter class variation

$$\sigma_1^2\ (C_{k_1} \cup C_{k_2}) = \frac{P(C_{k_1})P(C_{k_2})}{(P(C_{k_2})+P(C_{k_2}))^2}\ [\frac{1}{P(C_{k_1})} \sum_{z=T_{k_1+8}}^{T_{k_1}} z\ p(z) + \frac{1}{P(C_{k_2})} \sum_{z=T_{k_2+8}}^{T_{k_2}} z\ p(z)\ ] \quad (15).$$

Inter class variation

$$\sigma_A^2\ (C_{k_1} \cup C_{k_2}) = \frac{1}{P(C_{k_1}) + P(C_{k_2})} \times \sum_{z=T_{k_1-1}+8}^{T_{k_2}} [(z - m_{global}\ (C_{k_1} \cup C_{k_2}))^2 P(2)] \quad (16),$$

where $m_{global}\ (C_{k_1} \cup C_{k_2}))^2$ is the global mean among the C_{k_1} *and* C_{k_2}

2.3 Network Classifier

The outcome of the selective search is processed into a classifier for categorization. Several neural network architectures provide one step ahead effect in terms of accuracy and precision than the other classifier. For example, the convolutional neural network has many standard architectures like VGG16, VGG19, AlexNet, etc. These several networks pass the outcome of the selective search algorithm to prove the pre-eminent among them. The research has excluded the region of the interest bounding box as the investigation is only focused on the classification among the cancerous stages.

3 Result

In this research, The deep neural model was highly optimized and extended for medical field settings by using a large dataset of supervised pathological labels. The selective search is used to ease the task of the neural classifiers to outreach a better outcome. Finally, the resultants are compared to find out the best classifier for this performance. Among the standard architectures, These models are chosen for the research to do the final classification.

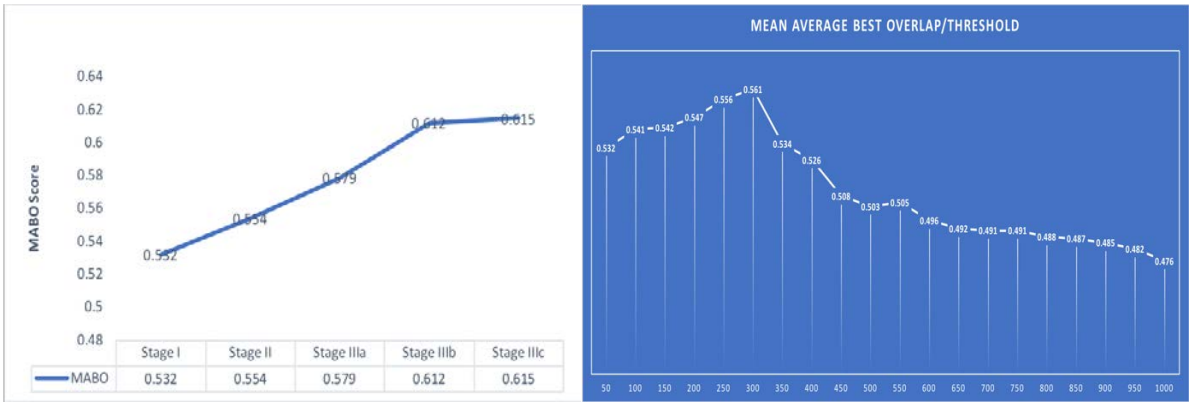

Figure 2: The mean average best overlap is calculated based on a different threshold value (right). The best score is generated at a threshold value of 300. The best value is standardized for calculation for scores of different lung cancer stage classification (left).

The average best overlap is a method to calculate the accuracy of object finding. It is the average of overlap on the ground truth of the class of the object with the proposed region of the object of the class.

$$\text{IoU (object-proposed, object-ground-truth)} = \frac{\boldsymbol{Area}(\textbf{object}-\textbf{proposed} \cap \textbf{object}-\textbf{groundtruth})}{\boldsymbol{Area}(\textbf{object}-\textbf{proposed} \cup \textbf{object}-\textbf{groundtruth})} \quad (17).$$

The average best overlap is the intersection of the proposed area of the object with its ground truth over the total area of their union. Finally, the mean average best overlap is the mean among overall average best overlap over all the classes. The MABO Score of stage 1 is less than the later stage due to its small size and position inside the lung. As these features are able to increase the score, It affects the output of the result. It scores only 0.532.however; the cancer stage 3 has larger in size, Proper shape, well-defined position and texture. Among the sub-stage of cancer stage 3, stage IIIb has secured 0.612 and stage IIIc has secured 0.615. As the stage of cancer passes, the visibility of cancer-affected cells can be clearly detected and easily classified.

Table 1: Cancer Stage TNM classification Accuracy vs error

Cancer stage		I	II	IIIa	IIIb	IIIc
Accuracy	%	0.78	0.86	00.86	00.87	00.91
error	%	0.22	0.14	00.14	00.13	00.09

The research is completely excluded box-based region generation in selective search object detection architecture. It only focuses on region-based selective search object detection. The MABO score can be improvised further by taking the output of selective search as input to various tested neural network implementations. The VGG19 has produced an overall accuracy of 0.84 for the classification process of lung cancer nodules.

4 Availability of Data and Material

Data can be made available by contacting the corresponding author.

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