# A Survey on Detection of Lung Nodules in Ct Scans Using SVM Classifier and ACM

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**Abstract:**
Early detection of lung cancer is the promising way of patient's survival which can be recognize by using Computed Tomography (CT) which is the technique in the detection of lung nodule compared to other imaging techniques. With the advancement of medical technology Computer Aided Detection Schemes (CAD) are developed [2]. It provides higher accuracy and performance rate. Here the lung CT images are taken as input, based on the support vector machine (SVM) it helps the doctors to perform image analysis. This paper focuses a study concerning automatic detection of lung cancer nodules by different methods.

**Index Terms - : Lung Nodules, Detection, Segmentation, Connectivity Recognition, Active Contour Model and SVM Classifier.**

## I. INTRODUCTION

Lung cancer is the deadliest cancer for men and the second deadliest cancer for women globally [1]. For instance, about 219,000 lung cancer cases are diagnosed in the US each year [2]. The specific abnormality that indicates lung cancer is growth of a nodule in the lung area. There are some different clinical nodule parameters that guide the radiologist in making a diagnosis of lung cancer. The first indicator is the shape of the nodule. A jagged shape nodule seems more likely to be lung cancer than a smoothed one. The second parameter is the texture of the nodule. If it is fatty, bony, watery or a mixture of different contents, the level of suspicion for lung cancer would be different. The third parameter is the location of the nodule. For instance, solitary nodules seem less likely to be lung cancer than vessel attached ones [3]. The growth rate of the volume of nodule is the fourth affecting parameter. For example, lung wall or fissure attached nodules typically are benign with volume-doubling period longer than 400 days.

Irregular shapes, complicated anatomical locations and sometimes low intensities of nodules lead to some problems for manual detection, segmentation, recognition and volumetric processes. Performing these processes manually is highly difficult, time consuming, and inaccurate. Having considered these issues, a complete system is required to perform these processes automatically.

Image cleavage is an crucial task of image processing. Its main intention is to detect and diagnose death threatening diseases. The main goal of distribution is to alter the representation of an image, which is more meaningful and easier to understand. Every fleck in an image is associated with a label and pixels with same label shows similar behavior.

## II. LITERATURE SURVEY

Table 1: Summary of Lung Nodule Detection and Classification in CT Images

| Author | Research Methodology | Classifier | Research Gap Analysis | Accuracy |
|---|---|---|---|---|
| Sarah Taghavi Namin et al.[11] (2010) | Fuzzy KNN for nodule detection and classification. Shape index calculation like Hessian matrix. | Fuzzy, KNN | This model did not verify dimension reduction method. | This method achieved sensitivity of 84% for nodule detection with approximately 10.3 False- Positive (FP) |
| **Author** | **Research Methodology** | **Classifier** | **Research Gap Analysis** | **Accuracy** |
| Shawn Lankton et. al.[13], (2008) | Active contours algorithm. Various internal energy measures like the uniform modeling energy, the means separation energy, and the histogram separation energy. | NI | In some cases Object segmentation is not Properly distinguished in terms of global Statistics. | 80% accuracy for segmenting heterogeneous images |
| M.Keshani et al.[14] (2010) | Active contour modeling. | Logistic Regression | This system has limitation in segmenting cavity nodule with irregular shapes. | All nodules (including solid and cavity) are detected with 89% accuracy and the number of FP is 3/scan |

| | | | | |
|---|---|---|---|---|
| Anthony Yezzi, Jr et al. [15](2010) | Coupled curve evolution models -Binary flow constraint and Ternary flow constraint. | NI | This model did not identify the constraints in global approaches. | 80% efficient |
| Steve Gunn 14 May 1998 | In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non- probabilistic binary line are classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). | SVM (Support vector machine). | The major limitation of the support vector approach lies in choice of the kernel." Burgess "A second limitation is speed and size, both in training and testing." Burgess "Discete data presents another problem..." Burgess | NI |
| Aly A.Fa rag et al.[9] (2010) | Bayesian supervised classier. Normalized cross- correlation similarity measure. | Naïve Bayesian classifier | The critical issue is to adequately discriminate between the nodules and non-nodules. | overall correct detection rate of 82.3% |
| Kazunori Okada et al.[17] (2005) | semi-automatic blob segmentation algorithm | Neural approach Classification. | LRT-based segmentation Framework is fundamentally restricted to the Gassiun spatial prior used in this study. | In average, this solution Runs in less than 3 seconds with a 2.4 GHz Pentium IV processor that is 3 times faster than the mean shift solution. |
| Alessandr a Reticoa et al.[18] (20 09) | A 3D dot-enhancement algorithm. Voxel-Based Neural Approach (VBNA) | NI | This model needs to identify nodules in low dose and thin slice CT images with low false positive rate. | CAD sensitivity in the 80−85% range are achieved with an average number of 6−9 FP per scan |
| Ms. Swati P. Tidke, et. al.[9] | For classification, SVM classifier is used. Support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification The basic SVM takes a set of input data and for each given input, predicts, which of two classes forms the input, making it a non probabilistic binary linear classifier. | SVM(Support vector machine) | Here the limitations are 1.A nodule diameter may be differed from a few millimeters 2. Nodules vary widely in density. 3. As nodules can be found anywhere in the lung region, they can be hidden by ribs and structures below the diaphragm, resulting in a large variation of contrast to the background. | NI |
| **Author** | **Research Methodology** | **Classifier** | **Research Gap Analysis** | **Accuracy** |
| Amal Farag et al.[16] (2010) | The Procreates approach. Active Appearance model. | NI | This model has limitations in the lung Nodules which appear in low dose Computer tomography of the human chest. | Data-driven Nodule models with orientation 0o -360o with step size 90 for all nodule for all nodule types, Sensitivity is 80% and Specificity is 74.5% |
| YuanjieZhe ng et. al.[1](2007) | Bspline-based no rigid transformation. | NI | This method failed to segment tumor in classical intensity. | 82% accuracy |
| D. Wu et al. [3] (2010) | Resilient subclass discriminate analysis (RSDA) Relevance vector machine (RVM) | NI | Accurate segmentation of pulmonary structures from abnormal parenchyma, caused by diffused lung diseases such as emphysema, is a challenging problem. | The overall accuracy is 86.3% |

| | | | | |
|---|---|---|---|---|
| C. Le et al. [4] (2008) | Fast self-fit segmentation refinement algorithm | NI | Due to a lack of contrast between lung and surrounding tissues, rule-based thresholding Method failed to segment these pathological parts of the lung. | Very effective for the separation lungs with a successful segmentation ratio 87.8%. |
| M.sil veira et. al,[5](2005) | Expectation- maximization (EM) algorithm | NI | This model identifies the limitations in ACM initialization. | Accuracy is81.3% |
| J.M. Kuhnigh et al. [6] (2006) | segmentation-based partial volume analysis (SPVA) | NI | This model Has difficulties in finding tumor which occurs frequently. | 84% accuracy |

***NI**: Not Informed

## III. Comparison Study

As per above mentioned literature survey table 1 information we generated the following 3 comparison graphs.

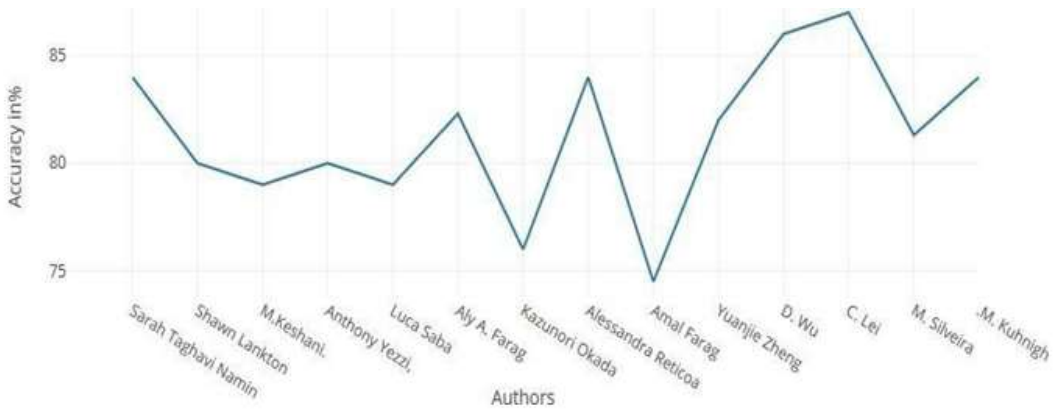


Figure 1.1: Accuracy Vs Authors

From the above graph we have seen the various authors and their related experiments. They have used various segmentation and classification algorithms and depends on them we got the specific accuracies. Most of the accuracies are the c.lei et al. [4] has got the highest accuracy 86% among them.

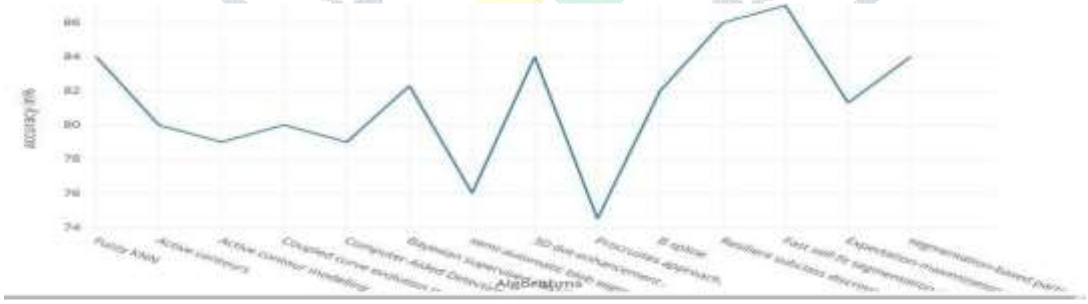

Figure 1.2: Accuracy Vs Segmentation Algorithms

From the above graph we have seen the relation between the accuracies and their segmentations. Here they have performed various segmentations like fuzzy KNN, active contours, coupled curve evolution, 3d hot enhancement, b-splice, fast fit segmentation, procreated approach, fast self-fit segmentations. These are the major segmentation algorithms they have used. We got 84% for fuzzy KNN, 80% for active contours modeling, 82% for baseman supervised algorithm, 86% for fast self-fit segmentation. Among these active contours has used the most.


Figure 1.3 Accuracy Vs Classification

From the above graph we have seen that few classification algorithms were used. A depends on their performances got related accuracies. Among the classifications SVM (support vector machine) is the most best and appropriate and got accuracy as 90%. SVM is used to classify large set of data and it has high importance in various experiments .hence in present we are trying to reach beyond their results.

As per above survey detecting non-isolated nodules, segmenting irregular shaped nodules and recognizing nodules with complicated anatomical locations are important issues of a CAD system of lung nodules. Although a number of methods have contributed to detecting and segmenting different kinds of nodules, recognition and even accurate segmentation of nodules, which are important, preprocess stages for lung cancer diagnosis and nodule volume try.

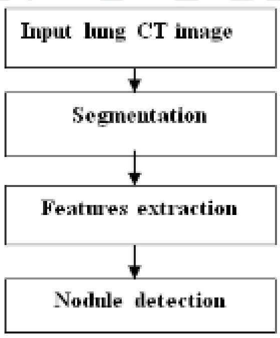


Figure 1.4: Methodology

In this paper, a novel method for lung nodule detection, segmentation and recognition using computed tomography (CT) images is presented. Our contribution consists of several steps. First, the lung area is segmented by active contour modeling followed by some masking techniques to transfer non-isolated nodules into isolated ones. Then, nodules are detected by the support vector machine (SVM) classifier using efficient 2D stochastic and 3D anatomical features. The primary goal is to make comparisons between different kernels in SVM like Polynomial Kernel, Gaussian kernel, Linear Spline and Radial basis Function.

## IV. CONCLUSION

By considering the overall existing experiments as literature survey accuracy is 90%. We have found that support vector machine is the more appropriate with 90% accuracy. In this paper we are suggesting to use of SVM with different kernels and with different techniques may be we get 100% accuracy.

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