

Classification of Lung CT Images using BRISK Features

B. Sambasivarao, G Prathiba

Abstract: Lung cancer is the major cause of death in humans. To increase the survival rate of the people, early detection of cancer is required. Lung cancer that starts in the cells of lung is mainly of two types i.e., cancerous (malignant) and non-cancerous cell (benign). In this paper, work is done on the lung images obtained from the Society of Photographic Instrumentation Engineers (SPIE) database. This SPIE database contains normal, benign and malignant images. In this work, 300 images from the database are used out of which 150 are benign and 150 are malignant. Feature points of lung tumor images are extracted by using Binary Robust Invariant Scale Keypoints (BRISK). BRISK attains commensurate characteristic of correspondence at much less computation time. BRISK is adaptive, high quality accomplishments in avant-grade algorithms. BRISK features divide the pairs of pixels surrounding the keypoint into two subsets: short-distance and long-distance pairs. The orientation of the feature point is calculated by Local intensity gradients from long distance pairs. Rotation of BRISK distance pairs is obtained using this orientation. These BRISK features are used by classifier for classifying the lung tumors as either benign or malignant. The performance is evaluated by calculating the accuracy.

Index Terms: Lung cancer, CT images, BRISK features, Classification, Accuracy.

I. INTRODUCTION

Lung cancer can be considered as a serious types of cancer in which cells in the lungs are partitioned uncontrollably. The person's ability to respire is reduced due to the growth of tumors in the lungs. Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC) are the two fundamental types of cancer that differ in terms of appearance, growth, spreading to other parts in body and how they are treated [1].

Lung cancer is mainly caused due to cigarette smoking i.e. 90% of lung cancers are attributed to usage of tobacco. Chemical compounds of 4,000 are contained in the tobacco smoke leading to cancer. Lung cancer occurs not only to cigarette smokers but also occurs to non-smokers by the intake of tobacco smoke that means accompany smokers. The

second reason for lung cancer is air pollution that means smoke from vehicles, industry, power generation and inhabitation of asbestos fibers at work place.

In 2012, lung cancer formed 20% of all deaths from cancer in the world that means 1.5 million deaths. As per the statistics of American Cancer Society, 224,210 new cases are present, resulting in 13% of all cancer diagnoses in the year 2014. In 2015, 218,527 people are estimated to have undergone lung cancer diagnosis by the centre for disease control in United States.

In 2016, according to American Cancer Society 1,685,210 new cancer cases diagnosed with early detections and 595,690 cancer deaths in the US. According to World Health Organization (WHO), an estimated 9.6 million cancer deaths in 2018 has resulted in which 2.09 million are due to lung cancer [2]. Signs of lung cancer differ and these signs are not constant. In few cases, there are usually no sign or symptoms in early stage. In some people symptoms, may include [1] continuous cough, fights for breath, blood during cough, chest pain and Loss of weight and fatigue. Lung cancer is categorized as different types based on growing characteristics and are broadly classified as benign and malignant. Benign lung tumor is not cancerous tumor and will not spread to remaining organs of the body. Normally these benign tumors are smoother, regularly shaped and grows slowly. These type of tumors need not to be removed and are not life threatening. There are different kinds of benign lung tumors which are hematomas and papillomas. Malignant lung tumours are cancerous and will spread to other parts of the body. These have irregular shape, rough surface and colour variation. Most of the lung cancers are malignant. There are different kinds of malignant tumors such as adenocarcinoma, squamous cell carcinoma and large cell carcinoma.

II. RELATED WORK

Khin Mya Mya Tun (2014) [3] proposed feature extraction and classification of lung cancer nodule using different techniques of image processing. Removal of deep noise is done by filtering with median filter, Otsu's thresholding for segmentation, Grey Level Co-occurrence Matrix(GLCM) for feature extraction and ANN (artificial neural network) especially feed forward ANN for classification resulting in accuracy of 90%. L. Punithavathy [4] (2015) proposed GLCM for second order statistical features extraction for Lung CT images and gives these features as input to the Fuzzy classifier for classification which gives accuracy of 85%.

Manuscript published on 30 April 2019.

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Atsushi teramoto [5] (2016) proposed classification of lung cancer by deep convolution neural networks gives accuracy of 70%. Manasee kurkure [6] (2016) proposed genetic approach (2016) this is used for preliminary diagnosis and detection of lung cancer from X-ray, CT (Computer Tomography) and PET (Positron Emission Tomography) images with optimization results. Navies Bayes is used for classification which gives accuracy of 80%.

Giovanni L.F. da Silva [7] (2017) proposed Convolution Neural Networks(CNN) for the classification of malignancy of lung nodules in CT images without computing the morphological and textural features which gives accuracy of 82%. Moffy Cripsin [8] (2017) used haralick features (these are the combination of Haar wavelet decomposing +GLCM), morphological operations for segmentation then used ANN for classification of lung cancer either benign or malignant

which gives overall accuracy of 88%.

Md.Rashidul Hasan [9] (2018) proposed statistical learning for lung cancer detection and classification using image processing. In this CT image is pre-processed and segmented by marker controlled watershed transform and then features are extracted. These features are given as input to the supervised classifier that is SVM which gives accuracy of 72.2%.

III. PROPOSED METHODOLOGY

This proposed methodology is shown in the below figure 3 in the form of flowchart. This flowchart explains the total procedure of this paper step by step.

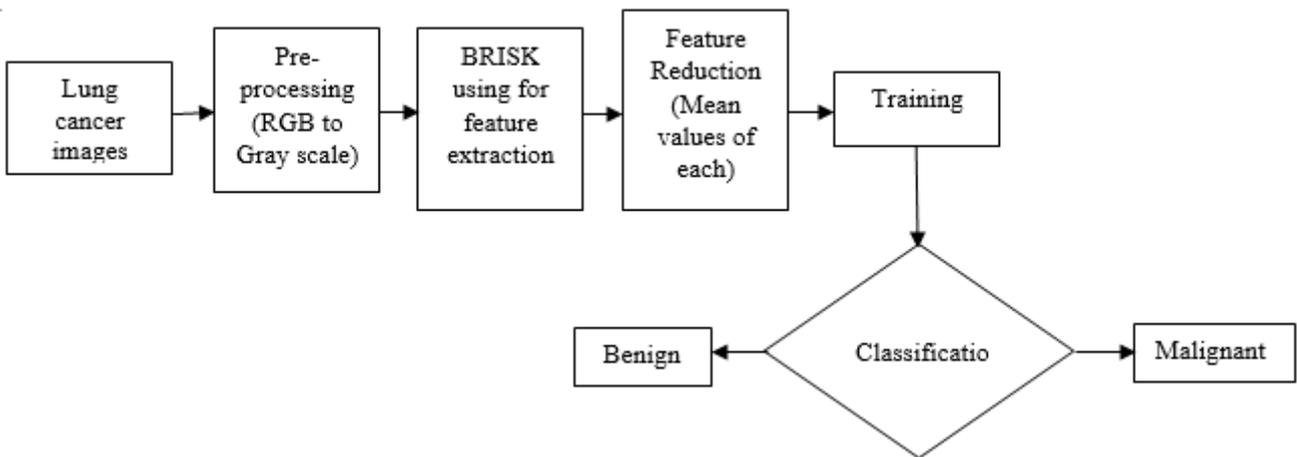


Figure 3: Block Diagram for Proposed Methodology

A. Image Database Collection

The images in the input database are downloaded from The Cancer Imaging Archive(TCIA) as SPIE database. These images are in the DICOM (Digital Imaging and Communications in Medicine) format having size of 512x512. The DICOM format is convert to PNG (portable network graphics) format. This database contains normal, benign and malignant types of images, database contains total 300 images, out of which 150 benign and 150 malignant are considered for the present work.

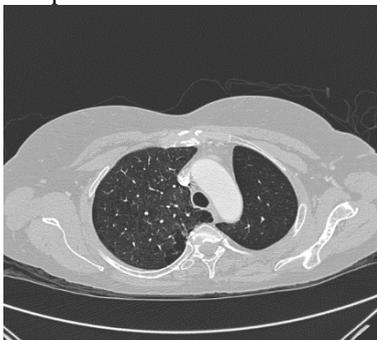


Figure 1: Benign Lung CT image

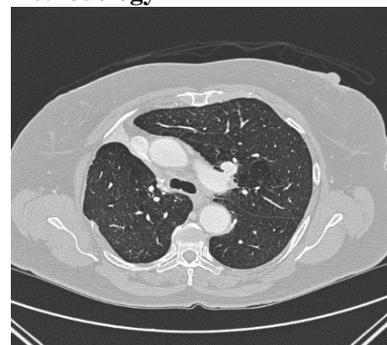


Figure2: Malignant Lung CT image

B. Preprocessing

The lung CT images are either three dimensional or two dimensional images. The 3D images is need to be convert into 2D format that means RGB to Gray scale format. Apply median filter for image denoising because all CT images are mostly affected by salt and pepper noise.

C. Feature Extraction

The malignant and benign CT images of lung are not visually distinguishable. Hence in this work, different feature extraction algorithms for extracting the features of both benign and malignant are used. In this paper feature extraction algorithm BRISK (Binary Robust Invariant Scalable Key points) is used on the lung images from the SPIE database.

BRISK (Binary Robust Invariant Scale Key points): BRISK proposed by Stefan Leutenegger [10] is used to detect the corners in scale space. This feature detection contains:

- Scale space Keypoint detection.
- Key point Description.

Scale space Keypoint detection:

Keypoint detection involves in detecting interest points in image and scale dimensions using a prominent criterion. The effectiveness of computation can be enhanced by identifying the keypoints in octave layers of the image pyramid as well as in layers in-between. Quadratic function fitting is used to calculate the location and scale of each keypoint in the continuous domain.

Create scale space: The scale-space pyramid layers in the BRISK structure consist of n octaves c_i , n intra-octaves d_i , for $i = \{0, 1, \dots, n - 1\}$ and typically $n = 4$. The original image is half-sampled consecutively to form octaves (corresponding to c_0). The layers c_i and c_{i+1} embed each intra-octave d_i in between them.

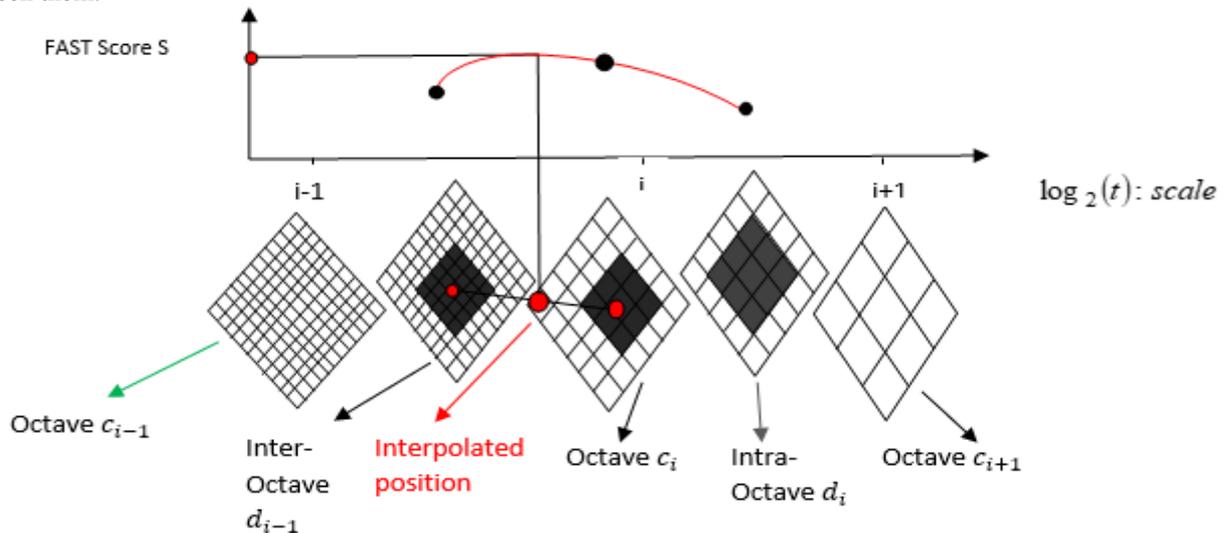


Figure 4: Scale-space generation with interest point

Compute FAST score across scale space: In BRISK, a 9X16 mask is frequently used that needs 9 alternative pixels in 16-pixel to be brighter or darker than the central pixel similar to the FAST criteria as shown in Fig.5. Octave and intra-octave are calculated separately. The maximum threshold T for FAST detection is obtained by considering the corner image points, denoted as FAST score s for each pixel. In such cases for obtaining the FAST score of intra-octave apply 5x8 mask on c_0 .

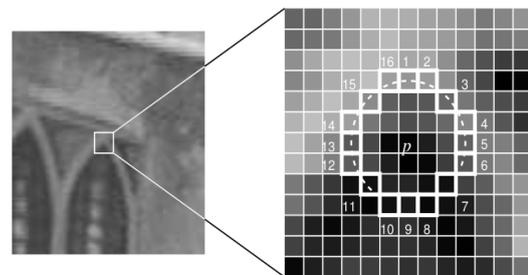


Figure 5: 9X16 masks for FAST score



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Pixel level non-maximal suppression: The thinning and detection of corners or edges based on pixels is done through non-maximal suppression which is obtained by identifying the points of interest on each octave and intra-octave using the same threshold T . The detection of maxima across the scale axis layer d_{-1} .

The intra-octave d_{-1} below c_0 octave can be obtained by applying the FAST 5x8 mask on c_0 . The scores in d_{-1} patch or may not be lower that score of point in octave c_0 as shown in figure 4.

A continuous refinement and subdividing of pixels for each detected maxima need to be considered along both the image and scale dimension.

The complexity of the refinement process can be reduced by fitting a 2D quadratic function in least squares to the three individual score-patterns yielding three sub-pixel refined prominent maxima.

The maximum values of final score and scale estimate can be obtained by fitting a one dimensional parabola with refined scores.

Classifier: In our proposed SVM (Support Vector Machine) is used for classification with grouping mechanism. That mean which images have similar features values those are divided into groups.SVM is a supervised learning algorithms that evaluate input data and patterns for classification.

Our input data is separated into training and testing modules. Proposed classifier is a binary classifier, it trained the data first and then classify the data into two classes with hyper plane separation with complex boundaries depending on support vectors.

In this paper used two class SVM and it is used for multi class classification also.

I. EXPERIMENTAL RESULTS

In this paper consider total of 300 images contain both benign and malignant lung CT images, out of these 300 images 20% of images are used for testing and remaining are used for training. By using median filter remove noise in the database images then extract features for all images with BRISK features such as location, orientation, scale, metric and count. Consider the mean values of all these features and import into MATLAB and then fed to the classifier for training and testing. Evaluate the accuracy, specificity and sensitivity for comparison of performance with different feature extraction algorithms.

By using BRISK, extract the feature points for the images in the database. It gives the Location, Orientation, Scale, Metric and Count by using all these feature points create the feature vector and assign the labels as benign and malignant. The strongest points for the input images are shown below.

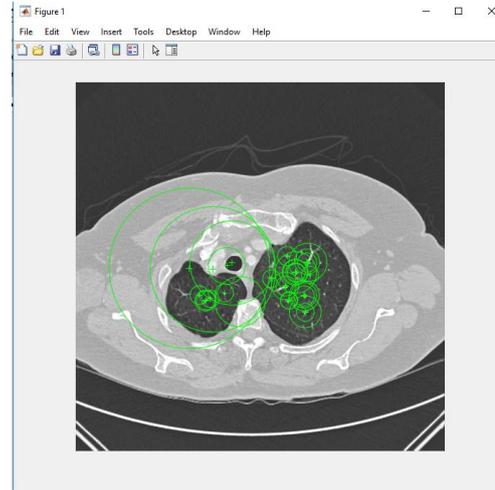


Figure 6: BRISK features of Lung CT image with 30 strong points

Table I: Accuracies of Haralick, SURF, FAST and BRISK.

| Feature | KNN classifier | SVM classifier |
|----------|----------------|----------------|
| Haralick | 65% | 68.8% |
| SURF | 72% | 78% |
| FAST | 78% | 79.33% |
| BRISK | 86% | 94% |

Our proposed BRISK features are compared with DWT (Discrete Wavelet Transform) and FAST (Features from Accelerated Segment Test) with help of accuracies with different classifiers. That results are shown in above table

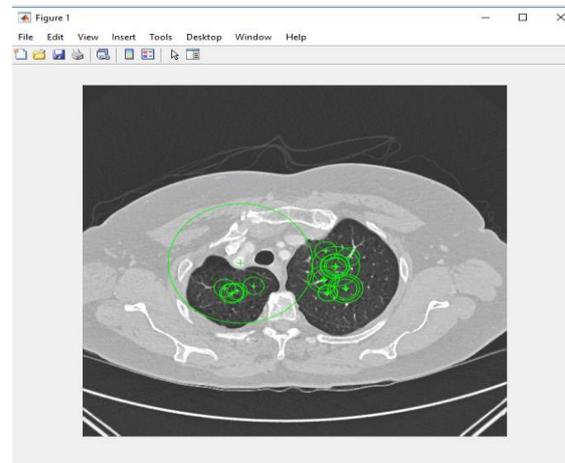


Figure7: BRISK features of Lung CT image with 20 strong points

The computational time and accuracies for BRISK features with SVM classifier using different kernels results are shown in figure8.

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Command Window

Accuracy of Linear kernel for BRISKFeatures is:
 98.6667

Accuracy of polynomial kernel for BRISKFeatures is:
 98.6667

Accuracy of Quadratic kernel for BRISKFeatures is:
 98.8889

Elapsed time is 46.833903 seconds.
fx >> |
    
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Figure8: Computational time and Accuracies for BRISK features

The accuracies of different feature extraction algorithms with classifier are represented in tabular column and graph as shown in figures 9-12 that depicts accuracies of different features with SVM using different kernels. Linear kernel gives better accuracy for Haralick features compared to the remaining kernels but quadratic kernel gives better performance for remaining features compared to the polynomial and linear.

Table III. Accuracies of Haralick Features, SURF, and FAST Features with SVM Classifier

| Features + Classifier | Accuracy(%) | | |
|------------------------|-------------|------------|-----------|
| | Linear | Polynomial | Quadratic |
| Haralick Features +SVM | 80.6 | 79.1 | 78.3 |
| SURF Features + SVM | 83.33 | 84 | 85.55 |
| FAST Features +SVM | 82 | 85 | 86.4 |
| BRISK Features +SVM | 98.6 | 98.66 | 98.88 |

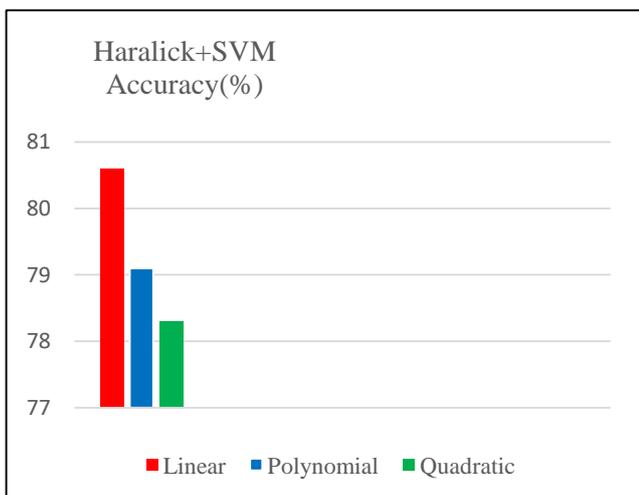


Figure9: Graph for accuracies of Haralick features with SVM classifier with different kernels.

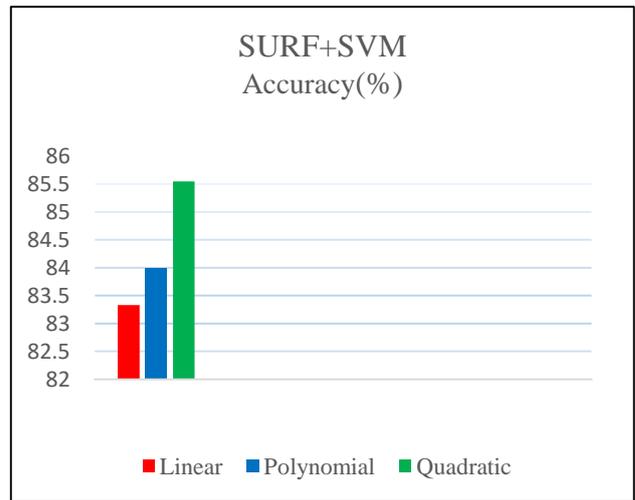


Figure10: Graph for accuracies of SURF features with SVM classifier with different kernels

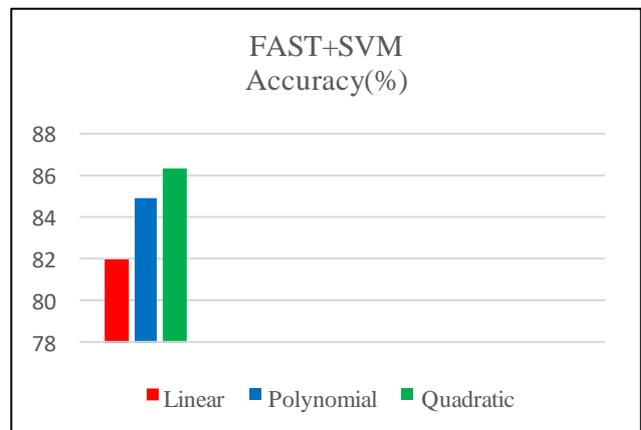


Figure11: Graph for accuracies of FAST features with SVM classifier with different kernels.

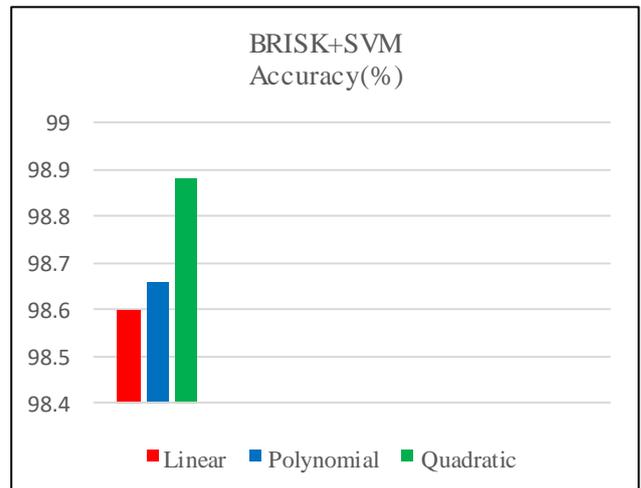


Figure12: Graph for accuracies of BRISK features with SVM classifier with different kernels.

II. CONCLUSION AND FUTURE SCOPE

Our proposed methods, developed benign and malignant classification of lung CT images are preprocessed by the conversion of RGB to gray scale image.



Three feature sets are extracted by using feature extraction algorithms. These features are reduced by taking mean values of feature points and then fed to the supervised classifier for calculating the accuracy. Finally proposed method is compared with Haralick, SURF and FAST with different kernels of SVM and calculated the computational time for proposed features with all SVM kernels. Compare the Linear kernel SVM with KNN classifier.

Future scope: To improve the accuracy and computational time optimization technique can be used for feature reduction.

These reduced features are given as input to the classifiers then get good accuracy compare to the existing results.

REFERENCES

1. <http://www.emedicinehealth.com/> for Lung Cancer symptoms, causes and treatment.
2. Lung Cancer Statistics from <http://www.webmd.com>.
3. Khin Mya Mya Tun," Feature extraction and classification of lung cancer nodule using image processing technique"; International journal of engineering research and technology (IJERT) ISSN:2278-0181 vol.3 issues,2014.
4. K. Punithavathy," Analysis of statistical texture feature for automatic lung cancer detection in PET/CT images", International conference on Robotics, Automation, Control and embedded system-Race 2105 ISBN:978-81-925974-3-0.
5. Atsu Atsushi Teramoto, Tetsuya Tsukamoto, Yuka Kiriyaame." Automated classification of lung cancer types from cytological images using deep convolutional neural networks", Biomedical research international volume 2017, Article ID:4067832.
6. Manasee Kurkure, Anuradha Thakare, "Lung Cancer Detection using Genetic Approach" in 2016.
7. Giovanni L.F.da silva, Aristofanes C.Silva,"Classification of malignancy of lung nodules in CT images using Convolutional Neural Networks", WIM-16⁰ Workshop de Informatica Medica, 2017.
8. Moffy Cipsin Vasv, Amita Dessai "Classification of Benign and Malignant Lung nodule using image processing techniques", International Research Journal of Engineering", ResearchGate:<http://www.researchgate.net/publication/328642003> and Technology (IRJET), vol.04, Issue:04, 2017.
9. Md.Rashidul Hasan, Muntasir AI Kabir, "Lung Cancer Detection and Classification on Image Processing and Statistical Learning researchgate, in 2018.
10. Stefan Leutenegger, Margarita Chiand Roland Y..Siegwart, "Binary Robust Invariant Scalable Keypoints", <http://www.researchgate.net/publication/221110715> in IEEE Conference on Computer Vision in 2011.
11. A. Melody Suzan, G. Prathibha "Classification of Benign and Malignant tumors of Lung Using Bag of Features ", International Journal Scientific & Engineering Research, Volume 8, Issues 3, March 2017. ISSN 2229-5518.

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