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# Detection of Distant Lung Cancer using Enhanced Transductive Support Vector Machines

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***Abstract:** Background: Cancer disease is the second largest disease after heart-attack in the world. Cancer is an abnormal growth of normal cell. Cancer is classified based on the cell type where it is mainly affected .There are different types of cancer like blood cancer, brain cancer, small intestine cancer, lung cancer, liver cancer etc. According to ICMR, among 1.27 billion Indian populations, the incidence of cancer is 70 – 90% per 100,000 populations and 70% of cancer is identified in the last stage accounting for high mortality. Though there are hundred form of cancer, the prognosis of bronchogenic carcinoma (lung cancer) is very poor because it can be identified only at a final stage. The beginning tumors are not more dangerous but the malignant tumors are more risky which spread to further portions of the body over blood stream or the lymph vessels. Prognosis and remedy is the biggest provocations in cancer for the medical field and physicians in the past few years. The CT scans support the doctors to detect cancer at early stage. When cancer is prognoses at benign stage, millions of human life across the world gets saved every year.*

***Method:** Noise in the CT scan input image is reduced by traditional adaptive median filtering and segmented by Region Based Neural Networks to extract a region of interest. To reduce the unwanted texture and noises and to detect wide-ranged images, Improved Canny Edge detector is implemented. The clinical characteristics of the patient were included as a feature reference. The considered features in clinical characteristics are status of patient smoking ,age of the patient, classification of tumor and T, N staging. Feature selection using Improved Glowworm Swarm Optimization and Classification Enhanced Transductive Support Vector Machines (ETSVM) is utilized to diagnose the distant metastasis of lung cancer.*

***Result:** Experimental results shows that ETSVM and Improved Glowworm Swarm Optimization achieved the best performance with an accuracy 90.7% and sensitivity 94.7%.*

***Keyword:** ETSVM, Enhanced Transductive Support Vector Machines, Lung Cancer, Carcinoma, CT scan, Computer Tomography, clinical characteristics, radiomic features, Improved Glowworm Swarm Optimization, Region Based Neural Networks, Adaptive median filtering.*

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## I. INTRODUCTION

A cone shaped pair of organ in human body is lungs, used for breathing. The lungs inhale oxygen and exhale carbon-dioxide, considered as primary function of a human system. A pair of lung consists of two sections, lobes and tube. A lung tube is known as bronchi continued to lungs through trachea. An uncontrolled growth in 1 or 2 lungs is lung cancer. Anomalous cell split faster to custom as a tumor cells. These anomalous cells do not grow in strong lung tissues. Tumors can be classified as two types, they are, benign tumors and malignant tumors. Cancer becomes very hard for treatment at advance stage. It is very hard to treat cancerous disease when it is extent to further parts. Treatments for lung cancer are surgery, chemotherapy, radiation and targeted treatment and immune therapy. The immunotherapy treatments include monoclonal antibodies, checkpoint inhibitors, therapeutic vaccines and adaptive T-cell transfers. But all these types of treatments may cause side effects. Screening of most lung cancers are based on the symptoms and symptoms are not very specific. The most common symptoms are severe cough, chest discomfort, shortness of breath, blood in spitting up, unexpected weight loss, back pain, loss of appetite and a continuous fatigue. Through three types of histological examination namely endoscopic, clinical and radiological, cancer is diagnosed based on their tissue abnormalities. Traditional screening of cancer costs high and blood waste screening will be cost effective, also supports to predict cancer at beginning stage. Early detection of lung cancer in stage 1 and stage 2 increases the chances of longevity but it is very difficult to predict at beginning stage as there are very less symptoms observed by the patient. Metastasis, later stage, spreading of cancer, is the cause of most cancer morality. When primary tumor grows at a higher rate, the cells are released from the origin organ to remaining parts of the body over blood stream or lymph vessels. These cells are named as circulating tumor cell. The circulating tumor cells, CTC, are shed into the blood stream as tumor grows and it is believed the cells initiate the spread of cancer, CTC, are rare, existing as only a few per 1 billion blood cells and highly efficient technology is required to capture CTC, which in turn helps to identify a cancerous cell at the beginning level before spreading. The cell which arises and forms as collection of cells is said to be cancerous cell. The benign cancerous cell is named as well differentiated and malignant is said to be poorly differentiated.

The sub types of NSCL cancer are ADC and SCC and LCC.

In the external part of the lung adenocarcinoma instigates and in the inward chunk of the lung, squamous cell carcinoma arises. A large cell carcinoma is a shapeless cyst without any proper identification feature. To control the carcinoma in different stages, various tests and treatments are followed. One among is pathological examination which includes small biopsy test or cytological samples examination. This diagnosing method does not determine the subgroups and display the harmfulness of entire tumor cell, which may leads to misdiagnoses of different levels of carcinoma.

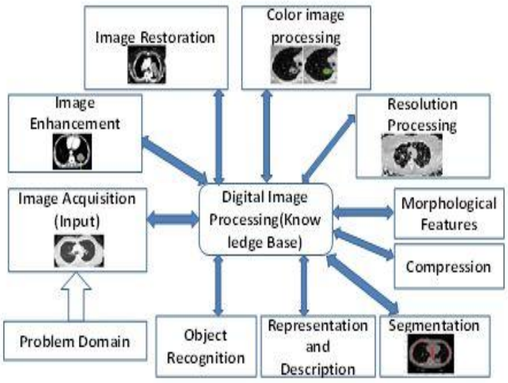



**Fig.1 Step-by-Step process of Digital Image Processing**

Hence advanced equipment's namely CT phantasmagorias progress the radiology's and further physicians ascertain inner arrangements of the organs to see their form, dimension, thickness and textures. Currently CT scans are broadly cast-off in clinics for the diagnosis of lung malignancy. The early stage of cancer can be detected by the traditional method called digital image processing, machine learning and deep learning.

## II. TECHNOLOGIES USED

Digital Image is a representation of picture elements which the combination of 0 or 1 known as pixels. DIP, Digital Image Processing, is a tool for processing or manipulating the picture element to improve the quality of picture or to extract information from the input image. The feature extraction form the image is done by computer algorithms. Digital image processing follows fundamental steps in processing the images, starting from image acquisition (input) to the object reorganization. In between the input – output, the image processing step involves are image enhancement (contrast). Contrasting, an image enhancement technique is spotted to guarantee the feature of concern in input images. Image restoration concentrates with enlightening the look of an image. Due to surge in the use of digital image through the internet, the color image processing is a gaining area in digital image processing. Inorder to decrease the image size, DIP follows a technique called image compression. The image components are extracted by morphological processing method to represent and describe the shape of the image. Then the image is processed into essential objects by image segmentation. The image is labeled based on its descriptors using object recognition. Finally the segmented data is converted into proper format to be processed by computer. The drawbacks with the traditional method, digital image processing are classification accuracy is still lacking in traditional method, series of stages which consumes more computational time and identifying and implementing of filters and algorithms is highly complex.

Machine Learning (ML) is a study of statistical models and algorithms to make the computer system to perform the task without unambiguously programmed. The learning methods have been applied to model the development and treatment of cancerous conditions. The key features are extracted from multifaceted data sets using ML tools, which divulge their status. The ML methods extensively pragmatic in cancer investigation for the progress of prognostic methods includes ANN, BN, SVM and DT for active and precise decision making. The expansions of listed prognostic methods are ANN, BN, SVM and DT. A proper validation is essential in day-to-day clinical practices, even though the usage of Machine Learning approaches increases the kind of cancer development.

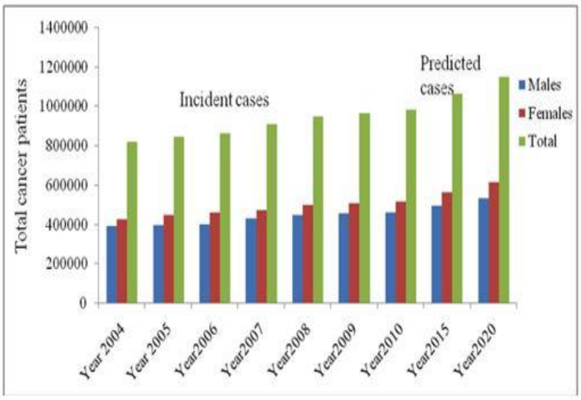



**Fig.2 Incidence rates of cancer in India from 2004 to 2020 on males and females [ICMR, 2006; ICMR, 2009].**

Deep learning is a member of the machine learning (ML) and artificial intelligence (AI) techniques. The deep learning architecture includes DNN and RNN which persistently improves the diagnosis of various lung cancers, such as breast, colon, cervical and lung cancer with good accuracy. Convolution neural Networks (CNN) a deep learning technique improved the chances of cancer detection.

## III. RELATED WORKS

Pratap, G.P., & Chauhan, R.P. (2016) [4] proposed the digital image processing methods for finding of lung carcinoma cells. According to the study, the main cause of illness is identified as tobacco utilization, hereditary components, ecological poisons and hand smoking. The treatment of cancer includes chemotherapy, radiotherapy, surgery, epidermal and open medication improves the survival rate of the patient. This paper proposed a diagnosing of schedule and critical stages from CT scan images with determined computational procedures with different noise elimination by the segmentation strategies and calculation using DIP. From the scan image of Computed Tomography, the lung carcinoma has been diagnosed using three different algorithms namely, median filter, watershed segmentation and high pass filter. The author handled the technique in two stages a) processing of distortion input image utilizing filter and segmentation b) morphological operations on CT picture. In last algorithm process only the growth influenced lung locale has been identified from CT scan image. The author reposes strategy can likewise be connected to the diagnosis of breast cancer and skin cancer.

Makaju, S., Prasad, P.W.C., et.al (2018) [5] proposed a computerized tomography images based detection of lung carcinoma. It is very hard for the physician to diagnose different types of carcinoma from Computed Tomography scan images only in medical imaging field, even though the CT scan imaging is proven as preeminent medical imaging methods. Thus, the machine learning techniques are helpful for physicians to classify cancerous cells precisely at primary stage. The focus of the research paper to examine different computer aided systems in order to suggest a new model with improvements from the computer aided systems limitation and drawbacks. The suggesting system considered to the finest method compare to computer aided system. The well identified drawbacks of Gabor filter in image processing technique is (i) very less feature only can extracted , (ii) does not support suggesting step like removal of noise ,smoothening of image which are used in prediction of cancerous cells precisely and (iii) classification of cancerous cells as primary and malignant stage is not accomplished. The known limitation using machine learning SVM classifier are a) the rate of accuracy not reached the expected level i.e. closer to hundred percentage. Thus it categorizes the carcinoma as benign or malignant and not classified as carcinoma level 1, 2, 3 and 4 based on the severity. The author determined the recent consideration models has no reasonable outcome of precision and classification of perceived lumps and new system is suggested for better accuracy and classification of various levels of cancerous as levels I,II,III and IV.

Abdullah, B., et.al (2017) [6] proposed a lung carcinomas finding technique by means of image processing method from computerized tomography scan image. The marker controlled watershed method and screening based segmentation, is implemented in the detection of image processing detection technique is based on marker controlled watershed, segmentations with screening. The technique functions under two phases namely segmentation in Phase I and enhancement in Phase II. In phase I, region growing and marker control watershed methods are utilized. In phase II, feature extraction and image enhancement using Gabor filter has been used for image enhancement. The segmentation phase produced a good result using marker controlled watershed method at running time. Abdullah, B concluded that color attribute in feature extraction can be implemented in the analysis of lung cancer.

Komura, D., & Ishikawa, S. (2018) [7] proposed investigation of histopathological analysis by means of machine learning approaches. The digital pathological image is analyzed by ML algorithm along with the solution to address some drawbacks with the system in analysis. Machine learning applications in numerical pathologies are CAD, CBIR and Discovering New Clinic Pathological Relationships. This paper addressed specific problems to Histopathological Image Analysis. The addressed problems are artifacts and color variations, huge image size, inadequate labeled image, WSI as order less texture-like image and various levels of magnification results in different levels of information.

Saad, M, & Choi, T.-S. (2017) [8] proposed a radiomics approach to identify the unclassified tumors of NSCL. NSCL (Non-Small-Cell Lung) cancer tumors are categorized as large cell carcinoma, squamous cell carcinoma and adenocarcinoma. About 21% of pathological reports are categorized into classified or non-classified as NOS owed to bad tumor diversity, which results in false analysis. The unclassified not-otherwise-specified tumor architecture is proposed to interpret the radiomic interrogation of molecular spatial variation. Different displacements and directions were mined and outlined in subgroup for twelve spatial descriptors. The outlined descriptors are utilized for the not-otherwise-specified tumors morphological clues and this outliner was erected as a conventional SVM classifiers. This is to state the molecular signatures of badly discriminated tumor. Thus 16 multi-class classifiers with higher accuracy and descriptor subset size of ranging 12-144 were testified. The unclassified Not-Otherwise-Specified membership matrix and model validated better Not-Otherwise-Specified reduction by correlation analysis model. In case of unrespectable tumors scanned for cancer therapy by biopsy examination then the membership matrix is utilized by pathologists and oncologist. Mahale, A (2017) [9] proposed a DIP methods to identify the lung carcinoma. The image processing techniques uses feature extraction and segmentation of lung Computed Tomography scan image. The Support Vector Machine algorithm in machine learning in implemented for feature selection and classification of lung cancer. MFPCM (Modified Fuzzy Possibilistic C Means) has been utilized for segmentation and Gabor filter for de-noising the Computed Tomography (CT) scan images. The need of ML methods improves the accuracy, time consuming and reduces the diagnosing cost of the patients. Also, a large set of data are trained by ML algorithms to regularly update the accuracy of the classifiers. Song, Q., et.al (2017) [10] proposed a DL techniques (Deep Learning) to classify the lung nodules from Computed Tomography images. For lung nodule classification, three types of deep learning techniques namely CNN, DNN, and SAE has been implemented.

The CNN, DNN, and SAE techniques are smeared on CT scan image for classification as benign and malignant lung cancer. The data's are calculated for LIDC-IDRI database and the CNN documented a virtuous recital results in position of sensitivity, accuracy and specificity. CNN shows good experimental results compare to DNN and SAE.A small NN (Neural Network) layers and small dataset utilized to improve the accuracy are considered as drawbacks .Hence for better results a CAD system can be designed for future research.

Teramoto, A., et.al (2017) [11] proposed a DCNN (Deep Convolution Neural Networks) for automated sorting of three different kinds of lung carcinoma namely, "adenocarcinoma", "squamous cell "and"small cell carcinoma" from cytological images. The automated lung cancer classification is a challenging task. The deep convolutional neural networks consist of 3 convolutional layers, 3 pool layers, and 2 completely linked layers for classification from microscopic images. The pixel images of 256*256 resolutions are cropped and re-sampled from microscopic images to avoid over-fitting. The evaluation result shows the better classification accuracy using the DCNN in cyto diagnosis.

## IV. MATERIALS AND METHODS

Image dataset: the dataset of CT scan image was collected from Kaggle / LIDC-IDRI database which includes 3, 47 and 330 images and each consist of images from a thoracic. CT scan, as well as the annotations provided by four radiologists. All the collected images undergo four stages for lung nodules detection, nodule segmentation, automatic feature extraction, risk source regression, and risk source thresholding. In the stage-1, the radiologists verify the CT scan to decide whether any lesion is a nodule whose diameter is higher than or much less than 3mm. in stage-2, the anonymous marks from other radiologists were provided so that a radiologist can draw a final conclusion, stage-3, risk source regression and stage-4 risk source thresholding.

Based on the four stages defined above, the lesions were reviewed and annotated by radiologist independently. To detect the lung nodules this database has been used for creating and testing CAD techniques. Since the training technique using unique pictures from the database is expensive. We propose to educate our CNN usage of smaller areas. First down-sample each image by half. We then utilized the data on the centroid of the malignant nodules and regarded these areas as the center of the region of interest (ROI). We cropped each malignant nodule picture into a 50*50 photo around the center of ROI after some rotation to reap 640 cancerous cases. For the non-cancerous cases, they selected the ROI interior the lung from the picture of non-cancerous cases and cut into 640 50*50 images. After all, we had 1280 picture in total as our dataset-1.

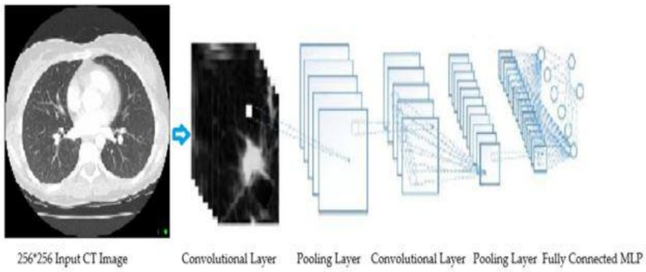
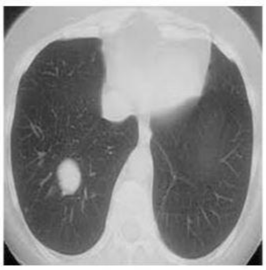
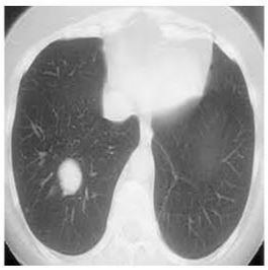



**Fig.3 Architecture of Convolution Neural Network with input CT Lung image.**

## V. PROPOSED SYSTEM

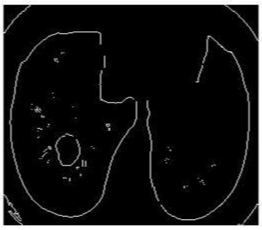
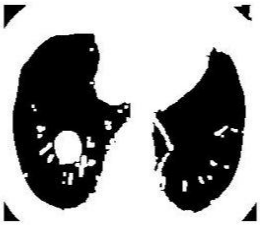
In the proposed system, Computed Tomography scanned picture is given as the input image. The CT scan image may consist of noise and blur. To reduce the noise in these images, the adaptive median filter was implemented. After removing the noise and blur in the CT scan image the contrast of the picture will be increased and at the same time morphological operations are performed to retrieve the information during the enhancement operation. Thus upon completion of morphological operation, region of interest is obtained by segmentation using Region Based Neural Networks. From the segmented image, edge detection is performed using improved canny edge detector. For better discovery of detection, canny implemented an edge detection algorithm which decreases false edge detection and deals sharper edge.Next stage is the feature extraction in which extraction takes place in two steps a) Includes texture Gabor ,volume and features as a complete lung cancer tumor radiomicsb) Also reference features are added as a clinical feature which consists of status of the smoking , age of the patient ,classification of tumor and T and N staging. After feature extraction process, feature selection is implemented using improved Glowworm Swarm Optimization. It is followed by classification. Enhanced Transductive Support Vector Machines (ETSVM) is utilized for classification. ETSVM method is utilizedforits high classification accuracy, high precision & recall and lower computational complexity.

## VI. EXPERIMENTAL RESULTS

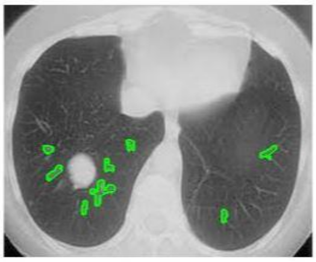
**(4) (5)**

**Fig.4Input Image Fig.5 Noise removed image using adaptive median filter**

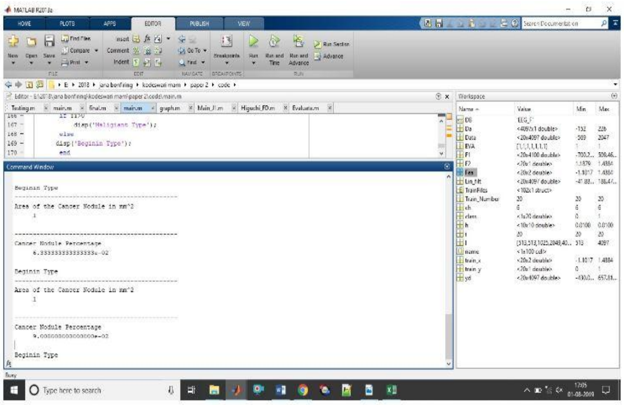
**(6) (7)**

**Fig.6 Segmented image Fig.7 Gradient mask**

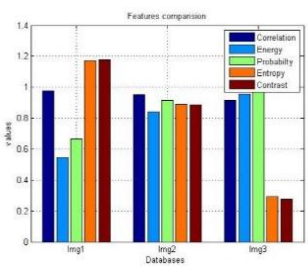
**(8) (9)**

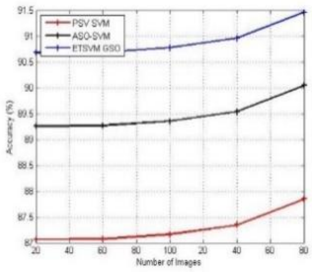
**Fig.8 Segmented Lung Nodule image, Fig.9 Possible location of cancer is traced by green boundary**



**(10)**

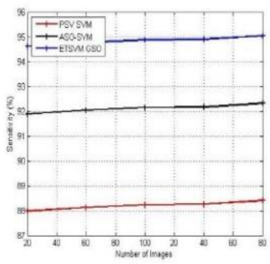
**Fig.10 classification of benign and malignant type**

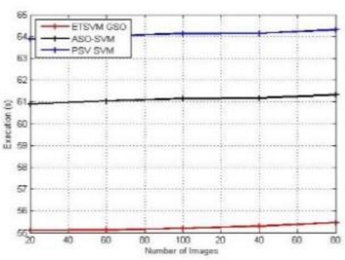





**(11) (12)**

**Fig.11 Feature comparison, Fig.12 Algorithm comparison with respect to accuracy**






**(13) (14)**

**Fig.13 Algorithm comparison with respect to sensitivity, Fig.14 Algorithm comparison with respect to execution.**

## VII. CONCLUSION

By using Enhanced Transductive Support Vector Machines classification technique and Improved Glowworm Swarm Optimization feature extraction the distant mechanism has obtained at high accuracy rate. The radiomic feature consists of texture Gabor, volume and wavelet feature of lung cancer. Along with this the clinical feature of the patient included. The clinical features involves age of the patient, status of the smoking habit ,classification of tumor and T-N staging at high precision and recall rate. Elimination of blurring and noise and increasing contrast, morphological operations are used for revealing details in enhancement operations at lower computational complexity with the accuracy of 83.15% and sensitivity of 82.56%.

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