Role of Computed Tomography Imaging for the Diagnosis and Classification of Lung Cancer using Machine Learning

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Diseases come in many forms, each posing its own unique set of difficulties for modern human civilization. The effects of cancer have been the most severe of all these disorders. For early detection of cancer and its effective treatment later on, many researchers are attempting to investigate and determine the disease's development pattern. In this study, a combination of image processing and machine learning is suggested for identifying and categorizing different types of lung cancer. Due to its rapid progression, lung cancer often proves fatal within a few weeks of its detection. In the current approach, databases of different types of lung cancer are established, and the photos included inside those databases are then classified into different cancer types based on the results of feature extraction. After that, the lung cancer in the photos is checked using a machine learning method that takes into account the segmentation strategy employed in digital image processing. The radiologists will benefit from this automated method since it will aid in data collection and analysis. Matlab will be used for all of the aforementioned tasks. The validity of the proposed system will be evaluated based on a number of metrics including Precision, Recall, True Positives, False Positives, True Negatives, and False Negatives.

Keywords: Image Processing, Lung cancer, machine learning, Matlab, Segmentation, disease.

1. Introduction

The cancer of the lungs is presented as the commonest type of cancer. Tumors account for almost 225,000 diagnoses, 150,000 deaths, and annual social insurance expenses of $12 billion in the U.S. [1]. It is also the most lethal sickness known to man (e.g. around 17% of deaths in the United States). Lung cancer poses the greatest risk to human health as it has the highest mortality rate among all malignant tumors. The occurrence of lung cancer is increasing rapidly, particularly in third-world nations [2]. A cancerous tumor implies that it has spread far. The first and second stages are lung-only cancers and the terminal phases are in which the tumour have metastasized to other parts of the body. Biopsies and imaging that are now used in diagnostic procedures, include CAT scans. As research into the development of imaging methods progresses, doctors now have access to a variety of information that may increase their ability to diagnose and analyze illness. For many people, the appearance of a nodule on their lungs is the first warning sign of lung cancer. Around 34% of pulmonary nodules are caused by lung cancer malignancy, and these nodules can have either a round or irregular shape. [1]. Detecting lung cancer in its early stages significantly enhances the chances of survival. However, it can be challenging to identify the early stages as there are often fewer symptoms and signs. It is critical to prioritize regular check-ups and screenings to ensure timely detection, which can be a lifesaving measure [1]. According to the Global Cancer Report Insights, over 1.83 million people were diagnosed with pulmonary disease in 2012, and close to 1.5 million advances [3]. Based on the most recent 2017 WHO data on lung cancer deaths, out of 1,584 deaths, Ethiopia accounted for 0.25% of total international arrivals [4]. The study of medical images is one of the most promising areas for identifying and diagnosing medical issues in various health problems. The purpose of medical image analysis is to identify and resolve medical issues by combining analysis methods for medical images that might spot potentially important and keeping any medical information [5].

Several types of medical imaging technologies are used for the screening and identification of cancerous cells by utilizing techniques like CAT (computerized axial tomography) scans, X-Ray (as in Mammograms), and Magnetic Resonance Imaging (MRI), Ultrasound, PET (Positron Emission Tomography) scans, and other imaging methods. That being said, Computed Tomography (CT) stands out above other imaging techniques. Computed tomography (CT) is useful for lung illness diagnosis because it may show every single cancerous cell or nodes [6]. It is widely acknowledged that there are limitations to using screening programs such as low-dose computed tomography (LDCT) for diagnosing lung cancer. These limitations are due to a shortage of trained personnel to meet the high demand and the issue of overdiagnosis [7]. This can be reduced with the help of a machine learning system approach that may be successful in lowering inconsistencies in diagnosis and enhancing it. Machine learning and artificial intelligence have been investigated for their potential in the early identification of cancer, which might lead to better treatment and ultimately save more lives. As a result of incorporating a biological image processing methodology with knowledge detection in data, a number of novel methods have been created and implemented. In this study, many machine learning algorithms were used to a lung cancer dataset to assess their accuracy, sensitivity, specificity, F1 score, and precision. Our research is to identify which machine-learning algorithms are most effective in detecting lung cancer in its early stages. A data collection for lung cancer was examined using Multinomial Naive

Bayes, Logistic regression, Random Forest, Ridge Classifier, and SGD classifier [6].

2. Review of Literature

This section gives a brief outline of how various techniques of machine learning are used for the detection of lung cancer. The Convolutional Neural Network (CNN) stands as a ubiquitous and highly utilized model in the realm of machine learning that spans across countless fields of study. The implementation of CNN has been fruitful in several fields of study and has advanced to cutting-edge technology in the fields of natural language processing efficiency, video classification, visual recognition, and categorization [7]. But, a better performance is still possible. Augmenting the invariability of image characteristics is a method for raising performance. Günaydin et al., (2019) implemented a categorization using a convolutional neural network of images and videos, producing several forms of pattern recognition and language processing. The fundamental advantage of a convolutional neural network is able to extract and identify crucial high points from existing data organically, free of external interference. Unlike other models, its convolutional and pooling layer do collaborative work with others on a border [8].

The pooling operation follows the convolution phase. The use of this collective effort helps reduce big regions and borders.. Because of this, prep time is lessened significantly, and also the chances of over-fitting are reduced. The action in the pooling layer consists of maximum pooling and average pooling. Combining means determines the typical area within the part the maximum pooling, the average pooling, and the focus. Weighted average calculates the typical area around the element hone-in, and maximum pooling calculates the space included by a bounding box [8].

[9] recognised problem including pair-wise categorization. Lung cancer close to the surface on repeated CT scans of lungs at the start of the disease's progression and lungs that aren't. Using techniques from computer-aided vision and deep convolutional neural network learning, both processes, in order to produce a reliable classifier. Precise pulmonary cancerous development classification might hasten or slow costs associated with checking for lung illness consistent early positioning and enhanced endurance. The goal is to construct an analytical tool that uses a computer. A computer-aided design system that stores information has been used to determine if a patient has lung cancer by analyzing a chest CT scan.

Finding pulmonary nodules is critical for early detection of lung cancer [1This paper uses a subset of CT images from the Lung Image Database Consortium (LIDC) dataset as training and testing data, completes data pre-processing by intercepting pixels, normalisation, and other methods, and realises data enhancement by rotating and scaling the data with the goal of expanding the pulmonary nodule sample library. When a Convolutional Neural Network (CNN) model is trained using the produced lung nodule sample library, pulmonary nodule recognition and segmentation can be accomplished, and their locations may be located. Lung cancer can be diagnosed by obtaining size and shape information from the disease's characteristic lung nodules. The results showed that the CNN trained on morphological features is better at detecting and diagnosing lung cancer.

As the lung cancer patient's histopathology is very important to the treatment process, Sakr [3] presented a deep learning approach to lung cancer diagnosis, making use of convolutional neural networks (CNN) with some tweaks to make them lighter and more efficient. After normalizing the input histopathology pictures, the CNN model was used to detect lung cancer. They tested the approach against the current gold standard in cancer identification using a database of histopathology photos that is accessible to the public. Based on the analysis of the results, the deep model proposed for identifying lung cancer has a significantly higher accuracy rate of 99.5% when compared to other techniques.

While many of the existing methods for identifying lung nodules have good sensitivity, they also introduce a substantial number of false-positive recommendations, making them practically unfeasible [4]. Mai et al. (2022) proposed a solution to the problem of false positives in their study. They introduced the Multi-Head Detection and Spatial Attention Network which uses multi-head detectors along with skip connections to collect parameters of various scales. This allows for the detection of nodules of different sizes, shapes, and types. The research team utilized a spatial attention module in training the network, which allowed it to distinguish nodules from noisy tissues in CT images with high accuracy, akin to how medical professionals do it. To further decrease the number of false-positive suggestions, they developed a lightweight yet effective false-positive reduction module that doesn't impose any limitations on the front network. Their extensive experiments revealed that our MHSnet outperformed state-of-the-art models, boasting a higher average FROC and a 2.64% lower false discovery rate. With the additional safeguard provided by the false-positive reduction module, the false discovery rate was reduced by 14.29%, which shows promise in reducing distracting recommendations in future detection tasks.

The majority of lung cancer cases begin in a single lymph node within the lungs and rapidly spread to other organs, including the brain [5]. Sultana et al.'s study [5] aimed to develop a method that could accurately categorize lung cancer at the benign stage. The study analyzed 15,000 CT scan images of lung benign tissue, lung adenocarcinoma, and lung squamous cell carcinoma. The team created ResNet-50, InceptionResNetV2, Inception-V3, and VGG-19 using a two-dimensional convolutional neural network (CNN) and a support vector machine (2-D SVM) to classify the three types of lung cancer. The models' performance was evaluated based on several criteria, including accuracy, precision, recall, and F1 score. Inception-V3 is currently the best model for transfer learning and CNN-SVM, with a validation accuracy of 99.13%. Additionally, Inception-V3 was the most effective model for accurately classifying lung cancer subtypes.

Successful therapy is more likely if cancer is captured early. Several studies have shown a correlation between the rising incidence of cancer and a general decrease in mortality. Lung cancer was found to be the second most dangerous ailment that results in the most deaths in recent research done in India and throughout the world, after heart disease [6].

Lung Cancer Detection

Many image processing methods have found use in the medical profession for illness diagnosis. There are four primary processes involved in the process of utilizing CT scans to identify lung cancer. Lung cancer diagnosis relies on a battery of tests, each with its own degree of accuracy [10]. First, the lung CT picture is pre-processed to get rid of any existing noises; next, a Region of Interest (ROI) is obtained by segmentation of the image. Finally, characteristics such as entropy, energy, and variance are extracted using feature extraction in the third stage [11]. The scan is then processed to obtain characteristics of the lung tissue, which are then processed by algorithms. Figure 1 depicts all the processes that must be taken in order to diagnose cancer.

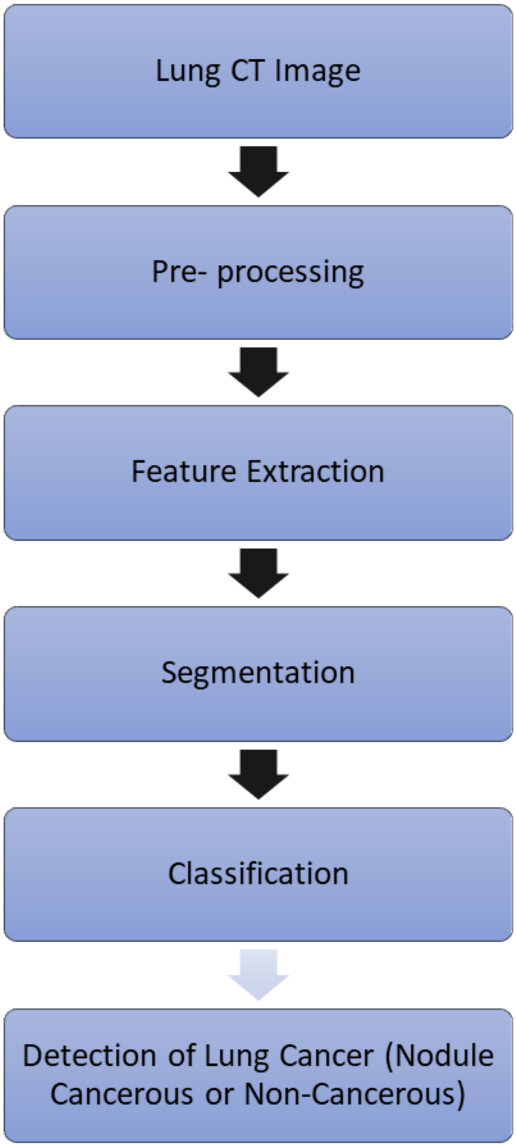


Figure 1: Step by step of detection process

Pre-Processing

During pre-processing, distortions are removed from the picture data, or other aspects are enhanced so that the data may be processed further with less difficulty. Also, the blueness must be eliminated, which necessitates reducing the effects of distortion in the imaging instrument, such as light fluctuation. It improves picture characteristics including line, border, and texture to separate images into their desired and unwanted components.

Researchers utilize a wide variety of filtering techniques to remove noise from images, and these techniques vary depending on the kind of noise being removed. Filtering techniques used in medical imaging include, but are not limited to, the following:

- Gaussian Noise: Normal distribution levels beyond which the picture is often invisible.
- Salt and Paper Noise: In the picture, there are occasional little black and white specks.
- Poisson Noise: In a Poisson distribution, the mean and the spread are the same. Noise is caused by the fact that image detectors don't respond in a straight line.
- Impulse Noise: Most of the time, this noise is caused by electromagnetic interference. It scratches up recorded disks.
- Speckle Noise: In ultrasound, CT scan images, and Synthetic Aperture Radar (SAR), it can be difficult to distinguish image parts due to numerous small reflections of waves. This interference, known as noise, occurs after the Gamma distribution. To reduce noise, there are two primary de-noising techniques available.

Image Segmentation

Segmentation of images is a crucial aspect of analyzing them, and it can pave the way for various other tasks. More specifically, many of the methods we use now for describing and recognizing images are based on how the results are broken up. Watershed segmentation techniques and Thresholding are used, but thresholding is the most effective tool for separating parts of an image. When compared to the gray level image, which usually has 256 levels, the segmented image created by thresholding takes up less space, processes faster, and is easier to work with. So, techniques like Thresholding, which have gotten a lot of attention, get a lot of attention. Watershed segmentation extracts the seeds by figuring out where in the image background objects are and if they are there[12-14]. After moving the markers to the regional minimums on the topological surface, the watershed algorithm is used.

Feature Extraction

It is used to find and separate parts or features of an image that are needed. Again, this is a very important step because it helps determine whether or not the image is normal or not. The following characteristics are the most important parts of the classification process and must be extracted. These are measured based on their area, perimeter, eccentricity, and average intensity. Using the features' definition as a guide:

1. Area: This scalar value indicates the precise number of the final pixel of a nodule. To determine this in the image, the areas of each pixel that are displayed as 1 in the resulting binary image are added together.

2. Perimeter: This is a scalar unit of measurement as well, providing the precise number of the nodule pixel's outline. The total of the connected outline can be determined from a registered pixel in the binary image.

3. Roundness: This measurement is for roundness or circularity or irregularity index, which is indicated by (I) is 1 for circular and is < 1 for other shapes, the assumption being increased circularityof the object.

Classification:

This kind of supervised machine learning uses a labeled sample of data to categorize new algorithmic results. Many classification algorithms, like Convolution Neural Networks (CNN), Back Propagation, and Support Vector Machines (SVM), use features taken from images [14-17].

Machine Learning Techniques in Lung Cancer

The field of machine learning (ML) is a subset of artificial intelligence (AI) that involves extracting new insights from existing data samples through two stages: (i) identifying unknown relationships within a dataset and (ii) using these relationships to make predictions about new outputs within the system. With the use of various approaches and algorithms, ML has become a promising area in biomedical research due to its ability to generalize and discern patterns within sets of biological data. Supervised learning involves mapping input data to the intended output based on labeled training data. In contrast, unsupervised learning does not require labeled instances and instead relies on the learning model to recognize patterns or groupings in the input data. Supervised learning can be used for classification problems, where the learning process organizes available data into discrete groups. Popular ML problems include regression and grouping, where information is transformed into a variable with actual values using a learning function. Clustering is a commonly used unsupervised data analysis technique where similar data points are grouped together and given descriptive names. Newly collected data can be placed into predetermined clusters based on the similarities they exhibit. The ultimate goal of ML is to develop a prototype that can assist with categorization, prediction, estimation, and other related tasks.

Semi-supervised learning is yet another type of machine learning technique, which is a combination of supervised and unsupervised learning. Both labeled and unlabeled data are combined so as to construct an appropriate learning model. Generally, when there are more datasetsunlabeled than labeled, then this type of learning is used.

Principal elements are the data samples; various features aggregate each sample, and multiple values are started in each feature. Moreover, knowing the specific type of data in advance allows the appropriate tool selection and techniques which can be used for analysis. Quality of data is reflected upon by some data-related issues, and through pre-processing steps, they become more suitable for machine learning. These include outliers, presence of noise, duplicate or missing data, and biased, unrepresentative

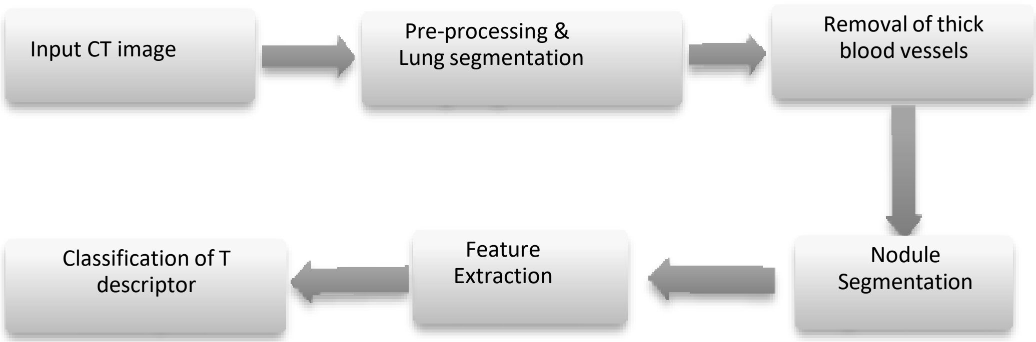
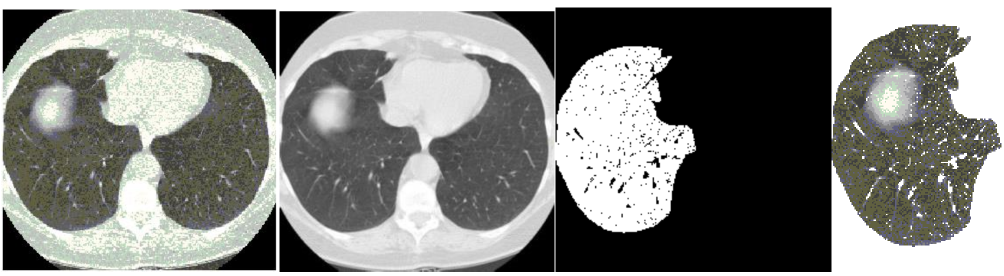


Figure 2 Flow Diagram of the Proposed System

Due to the possibility of noise in the supplied picture, preprocessing is required. The noise was eliminated with the use of a median filter. The Lung area is extracted and nodules are segmented using a multi-tiered single-click region growth approach. The elimination of blood vessels makes use of morphological operators. The nodule's T descriptor is determined after statistical characteristics are computed. Figure 2 shows the progression of the proposed computer-aided design. As a result of nodule segmentation, the search space from which different image attributes are derived is condensed, allowing for more efficient calculations. The identified area may be used to determine a number of useful metrics. As tumor size is the primary metric of concern, its area and diameter after segmentation to be determined. Figure 3 demonstrates the pre-processing results to determine the tumor and its position while figure 4 shows the tumor without blood vessels.



(a) (b) (c) (d)

Figure 3 Preprocessing results (a) Original Gray Scale image (b) MedianFiltered Image (c) Segmented left lung (d) Masked lung

(a) (b)

Figure 4 Segmentation results (a) Removal of blood vessels (b) segmented nodule

We conducted an experiment, and the results are shown in Table 1. The experiment included data from 8 patients. The size and number of nodules are the primary characteristics used to define the T stage. We use the staged T description. The data and recommended approach are shown in Table 6.5, demonstrating 95.89% accuracy and an estimated average error of +0.03mm.

Table 1 Sample Results with Eight Patients

PatientNo.	Experts Reading Diameter (cm)	Actual Result Diameter(cm)	IdentifiedStage
1	3.8	3.78	T2a
2	2.1	2.14	T1b
3	2.3	2.33	T1b
4	7.6	7.62	T3
5	8.2	8.19	T3
6	4.5	4.5	T2a
7	6.3	6.27	T2b
8	1.5	1.53	T1a

Results of T staging

Nave Bayes classifier outperforms SVM and SMO classifiers for T staging classification. Classification summary and performance metrics for all three classifiers using 23 sample pictures and seven variables are shown in Table 2. The number of successfully identified cases is greater for Naive Bayes compared to SMO and SVM classifiers, as seen in the table below.

Table 2 Summary of T staging Classification.

Measures	NaiveBayes classifier	SVM classifier	SMO classifier
Correctly Classified Cases	21	20	12
Incorrectly Classified Cases	2	3	11
Mean Absolute Error (MAE)	0.0436	0.0652	0.3007
Root Mean Squared Error (RMSE)	0.208	0.2554	0.3839
Relative Absolute Error (RAE)	11.7336	17.54	80.873
Root Relative Squared Error (RRSE)	47.859	58.76	88.32

Total Number of sample images : 23Total Number of Attributes 7

2. Discussion

CT imaging provides detailed cross-sectional images of the lungs, enabling radiologists to identify suspicious nodules, masses, or other abnormalities indicative of lung cancer. The ability of CT to capture anatomical structures with high resolution and sensitivity makes it an indispensable tool for the timely detection and subsequent identification of the stage of lung cancer.

A type of machine learning technique known as convolutional neural networks (CNNs) has demonstrated great performance in recognizing patterns and traits in medical images, including CT scans. These algorithms can develop a very accurate ability to distinguish between benign and malignant lung lesions by receiving training on massive datasets of annotated CT images. Additionally, CAD systems that have been combined with machine learning models can help radiologists analyze CT images. These systems act as a second opinion, providing automated analysis and highlighting regions of interest, which aids in reducing oversight errors and streamlining the diagnostic process.

Beyond diagnosis, machine learning algorithms can be leveraged to classify different subtypes of lung cancer based on CT imaging characteristics. This capability is valuable for determining optimal treatment strategies and predicting patient outcomes. Despite the promise of machine learning in lung cancer diagnosis, there are challenges to overcome, including the need for large and diverse datasets, potential biases, and the interpretability of algorithmic decisions. Further research is required to enhance the generalizability and clinical applicability of machine-learning approaches in lung cancer diagnosis.

3. Conclusion

In this study, we created a system that uses deep learning to automatically identify cancerous nodules in the lungs at an early stage. Thresholding, deformable boundary models, Region Growth, and other atlas-based and edge-based approaches may all be used for lung segmentation. The proposed method extracted the lung region using thresholding and morphological operations. The lung area is removed using morphological techniques. At first, the picture is converted from grayscale to binary. All input image pixels with intensities above the threshold are assigned the value 1, and all those with intensities below the threshold are assigned the value 0. Black-and-white pixel intra-class variation is minimized to get the threshold value.

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