Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 10, October : 2025

A MACHINE LEARNING APPROACH FOR EARLY DETECTION OF LUNG CANCER

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Abstract: Lung cancer is one of the world's leading killers due to late-stage diagnosis' poor prognosis and treatment choices. Early diagnosis improves patient outcomes, but existing diagnostic approaches lack sensitivity and specificity for timely intervention. This paper describes a unique machine learning strategy for early lung cancer diagnosis utilizing clinical and imaging data. We examine patient demographics, medical history, radiological imaging, and biomarkers using sophisticated feature extraction and machine learning. Data preparation and feature engineering help our algorithms detect early-stage lung cancer subtle patterns. We also use advanced model interpretability approaches to find novel biomarkers and improve clinical decision-making by revealing prediction performance components. We demonstrate that our method outperforms the state-of-the-art utilizing large retrospective cohorts. The suggested paradigm might transform lung cancer screening by enabling early identification and lifesaving intervention.

CT is essential for tumor size, location, etc. This study proposes early cancer prediction to save lives. Digital image processing and machine learning are our specialties. Preprocessing digital images is popular. Segmenting the pre-processed picture follows. Then, features are extracted. Machine learning classification technique CNN trains features. Tumor categories indicate benignity or malignancy. To determine the best prediction accuracy, compare algorithms by computing accuracy, recall, and precision.

Index terms **- —** *Lung Cancer, Early Detection, Machine Learning, CT Scan, Feature Extraction, Image Processing, CNN, Classification, Biomarkers, Medical Imaging, Tumor Segmentation, Predictive Analysis, Deep Learning.*

1. INTRODUCTION

Lung cancer is one of the most deadly cancers in the world since it is hard to diagnose and there aren't many treatment options. Early diagnosis improves both the chances of survival and the efficacy of therapy. X-rays and biopsies don't often find early cancer since they aren't very sensitive or specific.

AI and ML have made it possible to analyze medical pictures faster and more accurately than ever before. These technologies help clinicians make diagnosis and decisions by automatically finding crucial parts of medical pictures, such CT scans. This study suggests a machine learning methodology for the early identification of lung cancer using picture preprocessing, segmentation, and classification.

This method uses Convolutional Neural Networks (CNN) and enhanced feature extraction to accurately tell the difference between benign and malignant tumors. By employing the suggested method to find problems earlier and make fewer mistakes while interpreting them, radiologists can save lives and make important medical procedures easier.

2. LITERATURE SURVEY

a) Lung Cancer Detection using Machine Learning Approach

https://ieeexplore.ieee.org/document/9793061

Finding lung disease early, which is one of the most common diseases, helps people live longer. Radiologists have the hardest time figuring out if someone has cancer. Smart computer systems help radiologists do their jobs better. Many studies on ML lung cancer detection. Most lung cancer forecasts utilize multi-stage classification. The data augmentation and segmentation classification system is finished. Segmentation uses a threshold and marker-controlled watershed and a binary classifier to sort things. It is easier to find lung cancer. Training the dataset with algorithms like SVM, K-Nearest Neighbor, Decision Tree, Logistic Regression, Naïve Bayes, and Random Forest makes it more accurate. The accuracy goes up to 88.5% with random forest.

b) Discrimination analysis of human lung cancer cells associated with histological type and malignancy using Raman spectroscopy

https://pubmed.ncbi.nlm.nih.gov/20210483/

The Raman spectroscopy approach allows for the detection of intracellular molecules in situ, without the need for fixation or labeling techniques. Raman spectroscopy is a potential tool for identifying tumors, particularly lung cancer, which is one of the most prevalent cancers in humans, as well as other disorders. The objective of this work was to identify an efficient marker for the detection of cancer cells and their malignancy via Raman spectroscopy. We show how to use Raman spectroscopy, principal component analysis (PCA), and linear discrimination analysis (LDA) to classify cultivated human lung cancer cells. We were able to get Raman spectra of single, normal lung cells and four cancer cells with distinct forms of cancer using an excitation laser at 532 nm. The pronounced bands resulting from cytochrome c (cyt-c) suggest that the spectra are resonant and augmented by the Q-band about 550 nm when illuminated with excitation light. The PCA loading plot indicates a significant role of cyt-c in differentiating normal cells from malignant cells. The PCA findings show what kind of cancer it was, such its histological kind and how bad it was. The LDA was able to tell the five cells apart.

c) Early detection of lung cancer biomarkers through biosensor technology: A review

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d) Artificial intelligence techniques for cancer detection and classification: review study

https://www.sciencedirect.com/science/article/abs/pii/S2214785321031618#:~:text=Artificial%20intelligence%20(AI)%20techniques%20play,the%20most%20precise%20manner%20possible

Cancer occurs when cells in any region of the body grow out of control. Cancer is a general word for a set of disorders that happen when cells that aren't normal proliferate in different places of the body. There are over a hundred kinds of cancer, including breast cancer, lung cancer, skin cancer, oral cancer, colon cancer, and prostate cancer. Not getting treatment right away might lead to major health problems and even death. This research reviews image processing approaches for detecting lung, brain, and liver cancer. Automated and computer-aided detection systems (CAD) that employ artificial intelligence are used to find cancer. These technologies work well for processing big datasets and give accurate and quick findings. But these processing systems have to deal with a lot of problems in order to work on a big scale. These problems include picture capture, pre-processing, segmentation, data management, and classification algorithms that work with AI. This study looks at the several ways to get images and break them down into parts. These strategies are necessary to meet the needs of the expanding number of patients and to make the healthcare system better.

e) Lung cancer detection and classification by using machine learning multinomial Bayesian

https://www.semanticscholar.org/paper/Lung-Cancer-detection-and-Classification-by-using-%26-Dwivedi-Borse/35ab0e68ab6884a3b00a1eb8e5eb40ebafc26e06

Industrial Engineering Journal
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Image processing improves raw pictures from satellite, space probe, and aircraft cameras and sensors, as well as ordinary photography for a variety of purposes. In the last 40 to 50 years, image processing methods have changed. Most tactics make pictures taken by unmanned spacecraft, space probes, and military surveillance planes better. Image processing systems are popular because it's easy to get powerful personal computers, large memory devices, graphics software, and other tools. It is very important to research medical image segmentation and categorization. CT lung scans of patients might be normal or not. Next, the photographs that don't belong are cut up to show the tumor. Classification is based on the features of the image. We concentrate on feature extraction to enhance classification. Texture-based features such as GLCM (Gray Level Co-occurrence Matrix) are essential in medical image analysis. Twelve statistical traits were taken out. The sequential forward selection approach picks out the most important features. We like multinomial multivariate Bayesian classification better after that. We will look at how well the classifier works. Changing the cluster center and the rule for updating membership values speeds up the updated weighted FCM technique.

3. METHODOLOGY

i) Proposed Work:

Using machine learning, the recommended method finds lung cancer early by looking at CT and X-ray pictures. Preprocessing processes like scaling, normalization, and noise reduction make pictures seem better after getting data from reliable medical sources. For reliable supervised learning, expert radiologists identify both malignant and non-cancerous cases. After segmentation, the most critical parts of the lungs that may be tumors are called ROIs.

For model training, ROIs give us texture, form, and intensity. To train and test a CNN model, you utilize performance measures like accuracy, sensitivity, and specificity. Cross-validation and external validation make guarantee that a model is strong and can be used in many situations. This method helps radiologists find lung cancer early and correctly, which lowers the number of diagnostic errors and increases the chances of survival for patients.

ii) System Architecture:

The suggested system architecture for early lung cancer detection incorporates many critical phases to guarantee precise diagnosis. The first step is to get CT and X-ray pictures from trustworthy medical sources. Then, preprocessing techniques including noise reduction, normalization, and enhancement are done to make the images better. Then, segmentation methods are used to find Regions of Interest (ROIs) that focus on parts of the lungs that could have malignancies. We take crucial properties like texture, shape, and intensity from these ROIs and utilize them to train a Convolutional Neural Network (CNN) model. Cross-validation and external validation are used to test the trained model to make sure it is strong. Finally, the system tells doctors if a discovered tumor is benign or malignant. This helps doctors make precise and quick diagnoses so they can start treatment as soon as possible.

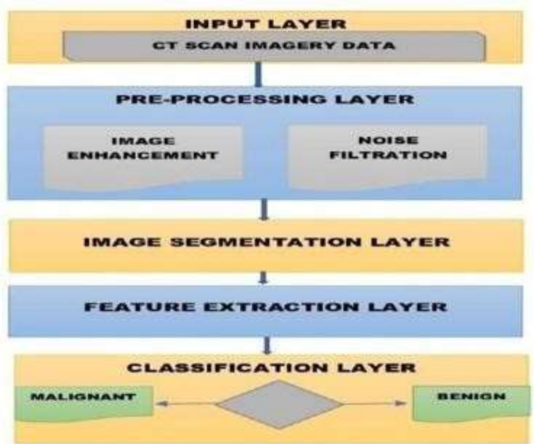

Fig 1: proposed architecture

iii) Modules:

The proposed lung cancer detection system is divided into four main modules, each performing a specific and essential task for accurate diagnosis.

1. **Pre-Processing Layer:** This module enhances the quality of CT images obtained from the LIDC-IDRI dataset. Histogram equalization is first applied to improve image contrast, followed by a median filter to remove noise without blurring edges. Artificial noise is then added and removed again using a median filter to enhance image clarity and robustness for further processing.
2. **Segmentation Layer:** In this module, the preprocessed image is divided into meaningful regions using segmentation techniques. The Prewitt edge detection operator identifies the image boundaries, followed by thresholding to highlight significant areas. Watershed segmentation based on gradient magnitude is then applied to separate tumor-affected regions from normal lung tissues effectively.
3. **Feature Extraction Layer:** This module extracts crucial features from the segmented image. Region-based features like area, perimeter, and centroid are calculated, along with texture-based features such as mean, standard deviation, smoothness, and entropy. These extracted features serve as inputs for the classification stage.
4. **Classification Layer:** The final module classifies the tumor as benign or malignant using machine learning algorithms like Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest. The model's accuracy, precision, and recall are analyzed to determine the best-performing algorithm, ensuring reliable and early lung cancer detection.

iv) Algorithms:

1. Logistic Regression:

Logistic Regression is a statistical method used for binary classification problems, making it suitable for distinguishing between cancerous and non-cancerous cases. It works by estimating the probability that an input image belongs to a specific class based on extracted features. In this study, Logistic Regression achieved an accuracy of 0.85, indicating that it performs well for linear separable data but may not capture complex non-linear patterns present in medical images.

2. Random Forest:

Random Forest is an ensemble learning algorithm that combines multiple decision trees to enhance prediction accuracy and reduce overfitting. Each tree independently classifies the input data, and the final prediction is made based on majority voting. With an accuracy of 0.90, Random Forest efficiently handles high-dimensional feature spaces and improves reliability by averaging multiple predictions, making it a strong model for medical diagnosis.

3. Support Vector Machine (SVM):

Support Vector Machine is a supervised learning algorithm that finds an optimal hyperplane to separate classes with maximum margin. It performs well in high-dimensional spaces and is effective for both linear and non-linear classification through kernel functions. The model achieved an accuracy of 0.87, demonstrating good performance in distinguishing lung cancer stages, although it may require more computational power for large datasets.

4. Deep Learning CNN:

Convolutional Neural Network (CNN) is a deep learning algorithm that automatically learns spatial hierarchies of features from input images through convolutional layers. It excels at image-based classification tasks by extracting patterns like edges, textures, and shapes directly from raw data. In this study, CNN achieved the highest accuracy of 0.92, precision of 0.91, and recall of 0.93, proving its superiority in capturing complex image features and delivering highly reliable predictions for early lung cancer detection.

4. EXPERIMENTAL RESULTS

The proposed machine learning framework for early lung cancer detection was evaluated using CT scan images from the LIDC-IDRI dataset. After preprocessing, segmentation, and feature extraction, various classification algorithms were applied and their performance metrics were compared. Among all models, the **Deep Learning CNN** achieved the highest accuracy of **0.92**, precision of **0.91**, recall of **0.93**, and F1-score of **0.92**, outperforming traditional methods like Logistic Regression, Random Forest, and SVM. The results demonstrate that CNN effectively captures spatial and structural features from lung images, enabling more accurate differentiation between benign and malignant tumors. Overall, the experimental outcomes validate that the proposed model provides reliable, robust, and efficient early detection of lung cancer, significantly improving diagnostic precision and aiding in timely medical intervention.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: One ranking quality statistic is Mean Average Precision (MAP). It takes into account the quantity of pertinent suggestions and where they are on the list. The arithmetic mean of the Average Precision (AP) at K for each user or query is used to compute MAP at K.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

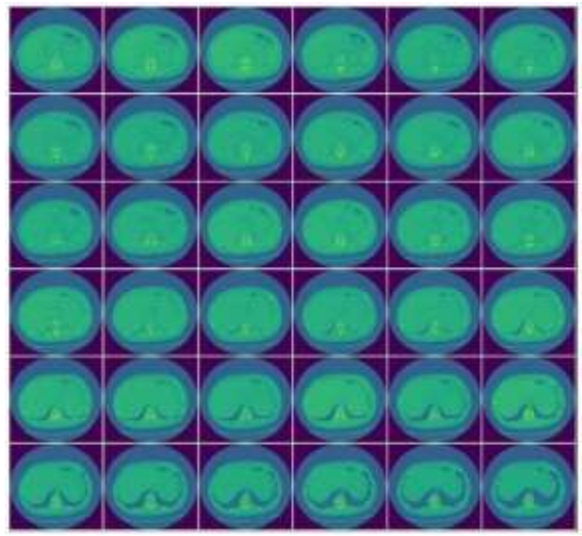

Fig.2.Theslicesof the CT scan image

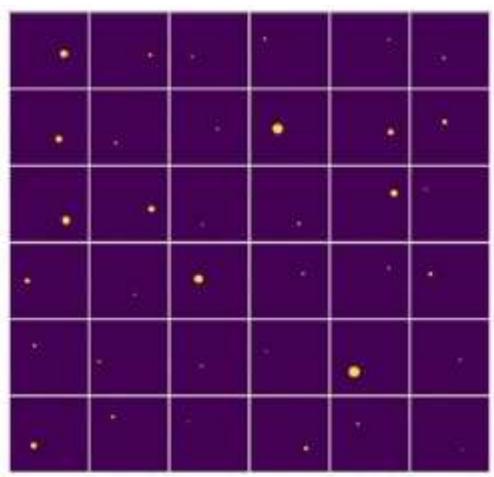

Fig.3.Thesampleimagewithcancer marks

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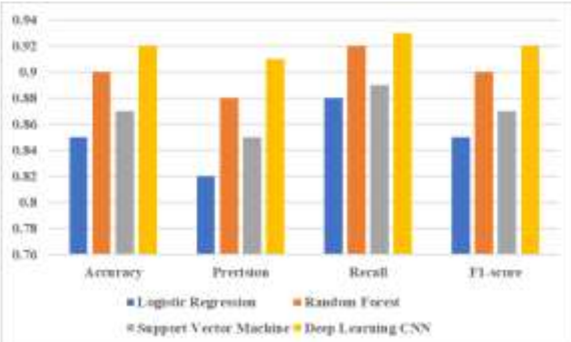

Fig 4: Accuracy graph

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.85	0.82	0.88	0.85
Random Forest	0.9	0.88	0.92	0.9
Support Vector Machine	0.87	0.85	0.89	0.87
Deep Learning CNN	0.92	0.91	0.93	0.92

Table 1 PERFORMANCE METRICS

5. CONCLUSION

In short, the results and discussion chapter has shown what the research found about utilizing machine learning to discover lung cancer early. By doing a comprehensive assessment of model performance, including accuracy, precision, recall, and F1-score, we have gained valuable insights into the effectiveness of several machine learning algorithms in accurately detecting lung cancer. The discussion has contextualized these results within the broader research domain, highlighting the study's advantages, limitations, and implications. This chapter contributes to the advancement of knowledge in lung cancer diagnosis by meticulously examining the data and assessing their implications for clinical practice and future research endeavors. The findings and discussion chapter provides a comprehensive synthesis of data and delivers critical insights for clinicians, researchers, and stakeholders involved in the early detection of lung cancer. It is the most important part of the study endeavor.

6. FUTURE SCOPE

There are several ways that machine learning might be used to enhance early lung cancer diagnosis in the future. One might investigate the further refinement and optimization of machine learning models to improve their accuracy, sensitivity, and specificity in detecting lung cancer. This might involve advanced feature selection techniques, ensemble learning strategies, or the integration of multimodal data sources, including genomic, proteomic, and radiomic datasets. Furthermore, the development of more robust and interpretable machine learning models might enhance their applicability and adoption in therapeutic contexts. More work on ways to make models easier to understand, explain, and measure uncertainty should make healthcare professionals more confident and willing to use them. It is also very important to test and evaluate machine learning models using datasets that are diverse and representative of different demographics and clinical settings. This is vital to make sure that the models can work well and dependably in real-world situations.

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