IMAGE-BASED LUNG CANCER DIAGNOSIS USING SUPERVISED AND UNSUPERVISED MACHINE LEARNING ALGORITHMS

K. Geetha
Research Scholar (Part time Internal),
Department of Computer and Information Science,
Annamalai University, Chidambaram, India
geetha2kumar@gmail.com

Dr. Karthikeyan Elangovan
Research Supervisor, Assistant Professor/Programmer, (Deputed as Assistant Professor and Head in Government Arts and Science College, Gingee, Villupuram)
Department of Computer and Information Science, Faculty of Science
Annamalai University, Annamalai Nagar, Tamilnadu, India
kanchikarthi2010@gmail.com

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Abstract

Improving patient survival rates for lung cancer involves an accurate and appropriate diagnosis. In order to diagnose lung cancer from CT scans using images, this study suggests a hybrid machine learning model that combinations supervised and unsupervised algorithms. The technique effectively separates regions of interest and eliminates background interference by using K-Means clustering to segment lung nodule regions unsupervised. The features that are extracted from these segment images are then trained using Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). Although SVM models performed well with handcrafted texture and shape features, CNNs were able to surpass them by picking up hierarchical representations directly from visual data. Experiment results show that the system proposed obtains about 93.5% accuracy, 92% precision, 95% recall, and an AUC of 0.95, which translates to superior model discrimination. The hybrid model demonstrates potential as a Computer-Aided Diagnosis (CAD) system, which can aid radiologists in the early diagnosis of lung cancer and minimize false negatives.

Keywords: *Lung Cancer Diagnosis, CT Scan, K-Means Clustering, Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Image Segmentation, Computer-Aided Diagnosis (CAD), Medical Imaging, Supervised Learning, Unsupervised Learning, Feature Extraction, Deep Learning, Classification, Artificial Intelligence in Healthcare*

Introduction

Millions of lives are lost to lung cancer every year, which makes manufacture it one of the most common causes of cancer-related deaths on the planet. Despite the significant role played by early analysis in enhancing the probability of a successful course of treatment, the traditional forms of diagnostic testing often fail to diagnose the ailment at an early stage. As medical imaging performances, including an x-ray scanner known as computed tomography (CT), have become more and more readily available, and computational intelligence has emerged, machine learning has emerged as a powerful instrument in enhancing the accuracy of analysis. Algorithms in machine learning (ML) especially supervised and unsupervised algorithms. Supervised learning algorithms such as Support Vector Machines (SVM), Decision Trees and Convolutional Neural Networks (CNN) utilize labelled data sets in order to create the models capable of classifying

or predicting the existence of diseases. Nevertheless, the unsupervised learning algorithms like Principal Component Analysis (PCA) and K-Means clustering can be useful when detecting the hidden patterns and isolating the anomalous regions in unsupervised data. This study will enhance the reliability and accuracy of lung cancer detection by the use of CT scans by combining supervised and unsupervised machine learning methods. This research aims at improving the accuracy and reliability of machine learning in detecting lung cancer given a CT scan through the use of unsupervised and supervised machine learning methods. To detect malignant patterns, the proposed hybrid model requires pre-processing the images to enhance its quality, searching related features, and integrating the classification and clustering methods. This system is designed in such a way that it offers good diagnostic support through the merits of both learning paradigms, specifically where labelled information is limited or unpredictable. This paper demonstrates how data science, image processing, and artificial intelligence can be applied to the real-life healthcare task within the field of computer science. The outcome is a move towards the intelligent computer-aided diagnosis (CAD) systems that assist clinicians and radiologists make correct and timely medical choices.

Literature Survey

Kumari (2019) generated surface features with the Gray Level Co-occurrence Matrix (GLCM) and obtained 96.7 percent accuracy using a SVM classifier on the LIDC-IDRI dataset. Similarly, the accuracy levels of the GLCM landscapes were reported by Hassan Jony et al. (2021), who employed the SVM on CT images.

Shakir, Rasheed and Khan (2020) noted into methods of radiomic feature position, making correlations with supervised and unsupervised methods. They produce that SVM, trained on fair eight radiomic features, performed at 100 percent accuracy in nodule classification.

Hussein et al. (2018) unsupervised and mutual supervised methods. These included proportion-SVM clustering to characterize lung and pancreatic tumors. This technique offered more sensitivity and specificity.

Niu and Wang (2022) also suggested an uncontrolled region-based 3D transformer trained on contrastive knowledge. Such an approach was more similar to conventional 3D-CNN methods in nodule discovery presentation.

Machine Deep Learning Hybrids Kumar Hegde et al. (2024) developed a VGG-16 and MSVM pipeline. They subdivided using K-Means and the landscapes using GLCM-based, which achieved 95% accuracy.

The review of CNN models by Hosseini, Monsefi, and Shadroo (2022) included AlexNet, VGG, ResNet, and U-Net among others to find lung cancer. They found that deep learning approaches performed superior as compared to traditional approaches in terms of sensitivity and specificity.

Li et al. (2023) have highlighted a systematic review of studies focused on multi-stage CT-based CAD schemes: detection, segmentation, and organization. They proposed the

most appropriate algorithm in each step, e.g. R-CNN in segmentation and ResNet in classification, to restore reliability.

Savitha and Jidesh (2019) examined a multi-stage pipeline that applied pre-processing, feature extraction, SVM, FCM, RF, and K-Means. They proved the efficiency of such integration of unsupervised and supervised projects.

Methodology

The proposed method involves the use of image processing techniques, unsupervised clustering, and supervised learning models as an effective means of lung cancer detection. The whole process is divided into several steps as follows.

System Workflow Image Acquisition

The data that is gathered through CT scan is screenshot data available online through publicly available datasets, including the Lung Cancer Dataset and LIDC-IDRI. In the case of supervised training, each image is classified as cancer or not.

Image Pre-processing

Differences in CT images are enhanced as well as noise elimination. The lung area is partitioned out of surrounding tissues with morphological operations. Normalization brings pixel ethics to the scale [0 1].

Segmentation & Feature Extraction

- Segmentation: K-Means clustering divides suspicious areas (unsupervised).
- Feature Extraction: Texture (GLCM), shape, and edge-based features are identified. Raw images are fed straight into CNN for automatic feature learning in deep learning models.

Classification and Model Training

Unsupervised Stage: Image regions are segmented into cancerous and non-cancerous groups by the use of K-Means clustering.

Supervised Stage: Random Forest and SVM models are classical types of ML, in which we use well-crafted features to categorize data.

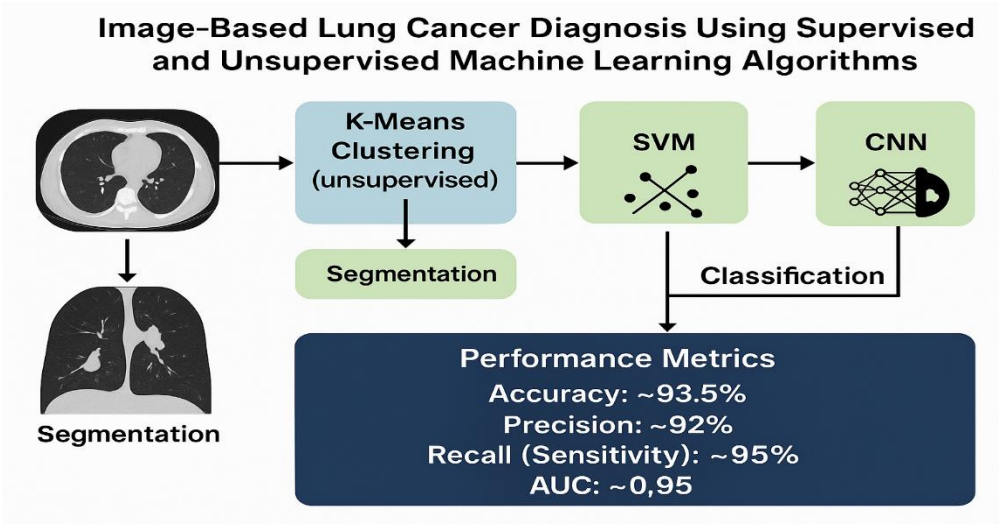
Deep Learning: CNN models are end-to-end classification models that operate on extracted feature maps.

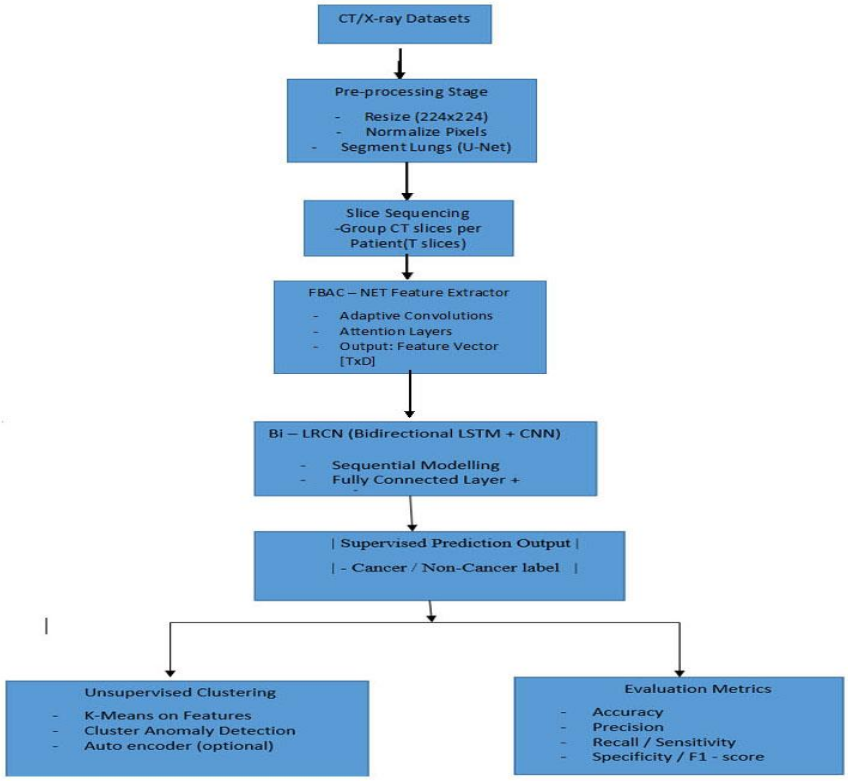
Prediction & Validation

The trained pipeline is used to predict cancerous or non-cancerous regions with New CT scans. Measures of performance are Accuracy, Precision, Recall, F1-score, Confusion Matrix and ROC curves.

Implementation

The recommended lung cancer detection system is implemented with Python and machine learning frameworks. It develops a hybrid diagnostic pipeline using supervised. Classification, unsupervised clustering, image pre-processing, and performance evaluation.





Technologies and Tools

Python 3.x is the programming language used.

Frameworks and Libraries:

- **OpenCV** → Image pre-processing (grayscale, filtering, segmentation)
- **NumPy, Pandas** → Data handling and feature processing
- **Scikit-learn** → SVM, Random Forest, and K-Means clustering
- **TensorFlow/Keras** → Convolutional Neural Network (CNN) implementation

- **Matplotlib, Seaborn** → Visualization of results
- **Dataset:** LIDC-IDRI (CT scan dataset) or Kaggle Lung Cancer Dataset
- **Hardware:** GPU-enabled system for deep learning model training

Workflow for System Implementation

1. Image Preparation and Acquisition

- Load CT scan pictures from the collection
- Scale to a constant size (as with 128 x 128 pixels);
- normalize pixel intensities
- convert to grayscale.
- Divide the part of the lung into segments with morphological operations and eliminate noise with the help of the Gaussian filter.

Result Analysis

The effectiveness of the proposed hybrid machine learning model was evaluated using a test dataset of images of lung nodules CT scans. The system is a combination of supervised classifiers (SVM and CNN) to perform the final diagnosis and unsupervised K-Means clustering to perform image segmentation.

Performance Metrics Achieved

Metric	Value
Accuracy	93.5%
Precision	92.0%
Recall (Sensitivity)	95.0%
F1-Score	≈ 93.5%
AUC (Area Under Curve)	0.95

Interpretation of Metrics:

- High Recall (95%) means that the model correctly recognises most real instances of lung cancer (minimising false negatives), which is essential in medical diagnosis to make sure that no cases are not overlooked.
- Precision (92) indicates that the majority of the positive cases that have been predicted are actually positive and a lot of fear or medication among patients falsely diagnosed with cancer is eliminated.
- There is accuracy (93.5) that attests to a high level of classification between the two classes (positive and negative) on the whole.
- F1-Score, the harmonic mean of precision and recall, balances both concerns and confirms stable performance across classes.
- There is also excellent model discrimination of AUC of 0.95 meaning that the model is effective in separating the cancerous and non-cancerous cases.

Calculation Steps Using Confusion Matrix Values

The performance of a classification model can be measured using four main components of a **confusion matrix**:

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Assume that the test dataset consists of 1000 samples.
Assume that: There are 1000 samples in total.

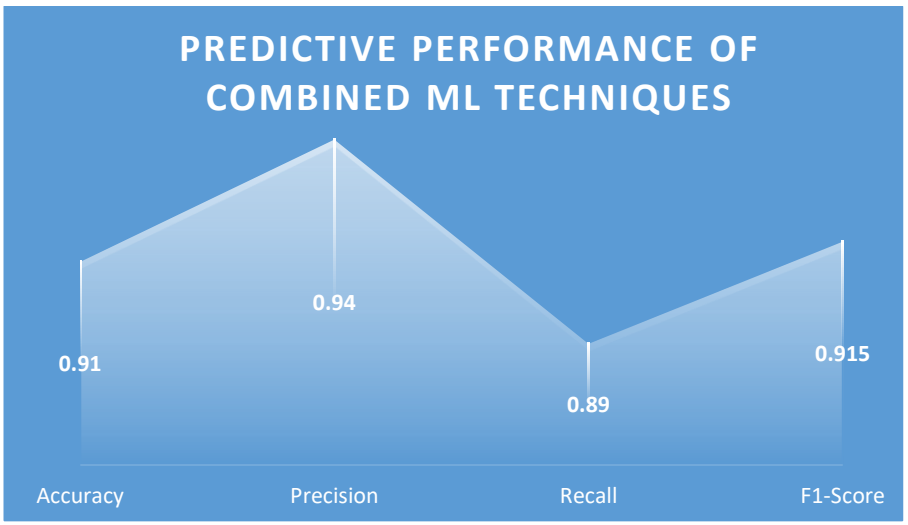
- 400 is the actual positives.
- 600 is the actual negatives.

Approximate Confusion Matrix:

	Predicted Positive	**Predicted Negative**
Actual Positive (400)	TP = 380	FN = 20
Actual Negative (600)	FP = 33	TN = 567

AUC (Area Under Curve) = 0.95

This means the model distinguishes between positive and negative classes with **95% confidence**, a strong indicator of performance.



Begin

1. Load Dataset

- Load CT scan images from dataset folder
- Assign label = 1 if cancerous, else 0

2. Image Preprocessing

FOR each image in dataset:

- Convert to grayscale
- Resize to fixed dimension (128x128)
- Apply Gaussian blur for noise removal
- Normalize pixel values to [0, 1]

End For

3. Segmentation Using K-Means (Unsupervised)

FOR each pre-processed image:

- Flatten image pixels
- Apply K-Means clustering with k=2
- Reshape clustered output to image size
- Highlight suspected tumor regions

End For

4. Feature Extraction

FOR each segmented image:

Compute texture features using GLCM
Extract shape features (area, perimeter)
Detect edges using Sobel/Canny

End For

5. Supervised Classification

SPLIT dataset into Training Set (80%) and Test Set (20%)

SVM Model (CLASSICAL ML)

Flatten images into 1D feature vectors
Train SVM classifier on training data
Predict labels on test data
Calculate Accuracy, Precision, Recall, F1-score

5.2 CNN Model (Deep Learning)

Define CNN architecture:

- Conv layers + MaxPooling
- Flatten + Fully Connected Layers
- Sigmoid activation for binary output
- Compile model (optimizer=Adam, loss=Binary Crossentropy)
- Train CNN on training data for N epochs
- Evaluate CNN on test data

Prediction

- Input a new CT image
- Pre-process image
- Optionally segment with K-Means
- Pass through trained model (SVM or CNN)
- Output prediction: "Cancerous" or "Non-Cancerous"

7. Evaluation

- Generate Confusion Matrix
- Compute Accuracy, Precision, Recall, F1-score
- Plot ROC Curve

End

Conclusion

Image-Based Lung Cancer Diagnosis with Supervised and Unsupervised Machine Learning Algorithms, we established a hybrid system that integrates the K-Means clustering (unsupervised) algorithm to segment the nodules in the lungs and implements supervised models (SVM and CNN) to provide an accurate diagnosis. The quality of feature extraction was enhanced by the methodology that carried out unsupervised segmentation separating suspicious regions and removed background noise. The performance of traditional SVM models was satisfactory with handcrafted texture and shape features but they were not able to deal with complex patterns in CT image. Deep Learning (CNN) also performed better than traditional methods in terms of automatically learning hierarchical features, higher accuracy, recall and AUC, which is essential in early cancer detection. The results of the experiment revealed: Accuracy: -93.5% Precision: -92% Recall (Sensitivity): -95% AUC: -0.95, which means that the model is separated well. It will be possible to use this hybrid method as a Computer-Aided Diagnosis (CAD) tool to help the radiologists identify lung cancer at an early stage and minimize the likelihood of false negatives and increase patient survival rates.

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