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High Precision Lung Cancer Detection Using Synergistic Weighting Segmentation and Swarm Optimized SVM Models

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Abstract

The development of malignant lung disease continues to be among the major reasons for death caused by cancer due to late detection and complications associated with the recognition of minute pathological changes in chest imagery. Differences in terms of the shape, intensity patterns, and structure of background tissues often limit the efficiency of standard automated diagnostic methods. An advanced diagnostic system is presented, which uses adaptive region segmentation and feature selection as well as optimal metaheuristics for the effective recognition of lung lesions through the use of computed tomography images. The method includes image pre-processing by applying the technique of contrast enhancement and noise elimination, along with weighted region segmentation that focuses on suspicious lesions while ignoring the rest of the anatomy. Various statistical, textural, and morphological features are then used to characterize the lesions. The performance of a support vector machine classifier is further improved with the use of swarm intelligence-based optimization. The use of this process in the optimization phase helps improve the process of feature differentiation and reduces uncertainty during classification in varying imaging conditions. Evaluation of the algorithm has been carried out using benchmark lung imaging data sets comprising both benign and malignant tumours. Various performance measures such as accuracy, sensitivity, specificity, precision, F1-score, and computational efficiency have been evaluated. The optimized system managed to obtain a performance level of 98.31% sensitivity, 97.83% MCC (Matthews Correlation Coefficient), 99.12% specificity, 98.91% AUC, and 98.44% F1-score, surpassing the performance of several other machine learning and deep learning algorithms used in the same application domain. These results indicate the significance of utilizing adaptive segmentation in combination with swarm-based classifier optimization. The proposed approach can serve as an effective decision-making tool in radiology and help physicians diagnose lung cancer at an earlier stage.

Keywords: Pulmonary Nodule Classification, Medical Image Segmentation, Swarm Intelligence Optimization, Support Vector Machine, Computed Tomography Imaging, Feature Extraction, Computer-Aided Diagnosis.

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Introduction

Despite being one of the common forms of clinical diagnosis, pulmonary malignancy is still a significant problem due to its high death toll and the problem faced when trying to determine abnormal tissue patterns early on during the development of the condition. One of the common methods used in the analysis of thoracic conditions is computed tomography imaging, which can be attributed to its capability in imaging small anatomical features at high resolution. Manual analysis of large numbers of CT scans is still very tedious and highly reliant on the technical know-how of radiologists, resulting in unreliable results (Masud et al., 2021). Shape irregularity of the lesions, low-contrast areas, irregular nodule borders, and image artifacts make the detection process more challenging (Ardila et al., 2019).

The rising accessibility of medical imaging data sets has led to an encouragement to develop intelligent computing methods for automated medical analysis. The application of machine learning and deep learning has shown great potential for discriminating imaging features and assisting in the process of making decisions in radiology (Alakwaa et al., 2017). Of all the methods available, the use of segmentation and classification plays a critical role in assessing the efficiency of the computer-aided diagnosis systems. Segmentation is important since it helps distinguish suspicious tissue areas from the rest of the body parts, thus aiding the feature extraction and classification phases (Pawar & Premchand, 2023). However, traditional segmentation methods have difficulties with distinguishing homogeneous tumours within CT images (Shafiei & Ershad, 2020).

Learning techniques based on optimization methods have proved to be efficient in solving problems of increasing the classification reliability and optimization of the classifier's parameters in the field of medical imaging processing. It is evident that swarm intelligence algorithms are able to determine the proper search area for classification training and feature selection (Canayaz et al., 2024). The support vector machine models have been widely used for diagnostic purposes due to their high capacity to generalize and solve problems with non-linear decision borders, especially in the case of small-sized and unbalanced data samples (Ge & Zhang, 2023; Shakir et al., 2020).

Recently conducted research has also revealed the significance of the hybrid model comprising preprocessing, segmentation, feature extraction, and optimization-supported classification stages to form an integrated architecture for pulmonary disease diagnosis (Jiang et al., 2025). Despite notable advancements in this field, current models continue facing certain difficulties associated with incorrect positive predictions, high computational cost, and decreased robustness. For this reason, there is a need for developing an intelligent model that would ensure accurate lesion localization and reliable classification at the same time (Venkatesan et al., 2024) .

In this study, an integrated computational model has been presented for the detection of abnormalities in lungs based on adaptive segmentation, discriminative feature extraction, and optimization-based classification through support vector machines. The main objective behind the methodology described is the enhancement of accuracy in the identification of regions of interest and optimization of parameters of the classifiers through swarm intelligence.

Key Contributions:

- Created a holistic approach to pulmonary image analysis based on adaptive segmentation, feature extraction, and optimized classification.
- Suggested a method of weighted region enhancement that helps to locate the boundaries of lesions in complicated CT images more accurately.
- Used the swarm intelligence optimization technique to enhance the efficiency of support vector machines and minimize classification error.
- Obtained impressive results in all of the used metrics, such as sensitivity, specificity, F1 score, MCC, and AUC.

The paper is organized such that there is an orderly sequence of moving from defining the problem to validating it through experiments. In Section I, the clinical significance and challenges associated with analyzing images of the lungs are presented. In Section II, computational approaches employed in detecting abnormalities in the lungs are discussed. The processing procedure is described in Section III in its entirety, along with preprocessing, adaptive segmentation, feature extraction, and classification optimization. Section IV presents the evaluation of the proposed framework on benchmark datasets. Lastly, Section V highlights the major contributions of this study and future work direction.

Literature Review

Recent developments in the field of pulmonary image processing have shown the increasing significance of intelligent diagnostic systems for improving lesion detection accuracy using CT images. Previous works have examined various approaches using different combinations of segmentation, feature extraction, optimization, and classification methods.

A hybrid deep learning model incorporating both convolutional neural networks and image processing was developed to increase efficiency in the detection of lung abnormalities from CT images. It was discovered that by enhancing the preprocessing technique, the feature extraction process improved, along with reduced segmentation errors (Wadhwani & Tembhurne, 2026). Another study paper proposed that using multiscale segmentation techniques along with morphology-based techniques would be helpful in detecting abnormal pulmonary nodules (Asiri et al., 2025).

In addition to that, machine learning algorithms incorporating optimization algorithms have also found extensive application in medical imaging technology systems. One such algorithm incorporated into support vector classification was the swarm intelligence optimization algorithm, which helped increase classification accuracy by varying the value of kernels and features in prediction. It has been observed that this combination helped improve classification accuracy and sensitivity significantly more than the conventional use of a support vector classifier (Kumari & Goel, 2026). Similarly, another method where particle swarm optimization was combined with texture feature analysis proved better in detecting lesions (Shakeel et al., 2020).

While other studies focused on exploring diverse approaches to feature extraction for pulmonary disease diagnosis, the radiomics approach using statistical and textural feature extraction from lung regions proved to be able to differentiate between benign and cancerous lesions (Bera et al., 2019). Moreover, the wavelet transformation technique combined with machine learning techniques demonstrated excellent performance in identifying abnormalities despite the presence of image noise or lesions of various sizes (Kumar et al., 2015).

Furthermore, deep learning algorithms have also proved their effectiveness for the diagnosis of pulmonary imaging. This includes a deep learning-based encoder-decoder segmentation architecture used for identifying lesions in the lungs that were capable of locating suspect regions as well as preserving structure on CT scans (Pezeshk et al., 2018). Another example is the development of a classification model using convolutional and transfer learning approaches for the classification of lung nodules (Nasrullah et al., 2019).

The application of meta-heuristic optimization approaches has been widely adopted to improve classifier performance and efficiency. The approach that involved beetle swarm optimization and classification using kernels gave very low levels of false positives and efficient convergence while optimizing the classifier (Xie et al., 2020). Another study on intelligent system design, which included the process of adaptive segmentation and optimization-based classification, led to good diagnostic results for many types of images (Velmurugan et al., 2025).

As can be understood from the analyzed literature, segmentation, discrimination of feature extraction, and classification through optimization are important aspects that must be incorporated in a computational system that is used in the analysis of pulmonary images. Although they provide good performance levels, current methods of image analysis exhibit some drawbacks, such as poor definition of boundaries, sensitivity to imaging noise, and increased instances of false positives in heterogeneous CT studies. Similarly, most traditional approaches exhibit certain weaknesses that relate to parameterization and classifier stability amidst complex pulmonary structures. These circumstances demonstrate the need for an integrative computing approach that assists in optimizing classifier consistency and lesion localization through adaptive weight setting and intelligent optimizations.

Proposed Methodology

Overall Framework

The proposed framework is for improved localization of lung lesions using computed tomography images, using the following steps: Preprocessing, adaptive segmentation, discriminant feature extraction, and efficient classification algorithms. Below is the full process flow of the proposed framework architecture shown in fig. 1. The key objective of this framework design is aimed at improving the accuracy of lung lesions localization and reliable classification of lung lesions by combining weighted segmentation and swarm vector machine learning algorithms. Firstly, CT images of the chest are collected and subjected to preprocessing. This involves improving the quality of images while reducing noise and intensity variations by using median filtering and contrast improvement techniques.

Segmentation after the preprocessing stage is done by adaptive weighted segmentation to extract potential regions from the lung organ. Segmentation technique makes use of edge intensity, texture distributions, and regional contrast

information to develop the weighted map that enables accurate extraction of the lesion boundaries. After the extraction of the regions using the above procedure, they are post-processed in order to eliminate all the unnecessary elements and keep only the necessary properties. Then, statistical characteristics, texture characteristics, shape characteristics, and various higher-order regional characteristics are extracted in order to give an overall description of the behaviour of the lesions. Finally, they are given to the support vector machine classification algorithm, which is optimized using a swarm intelligence approach.

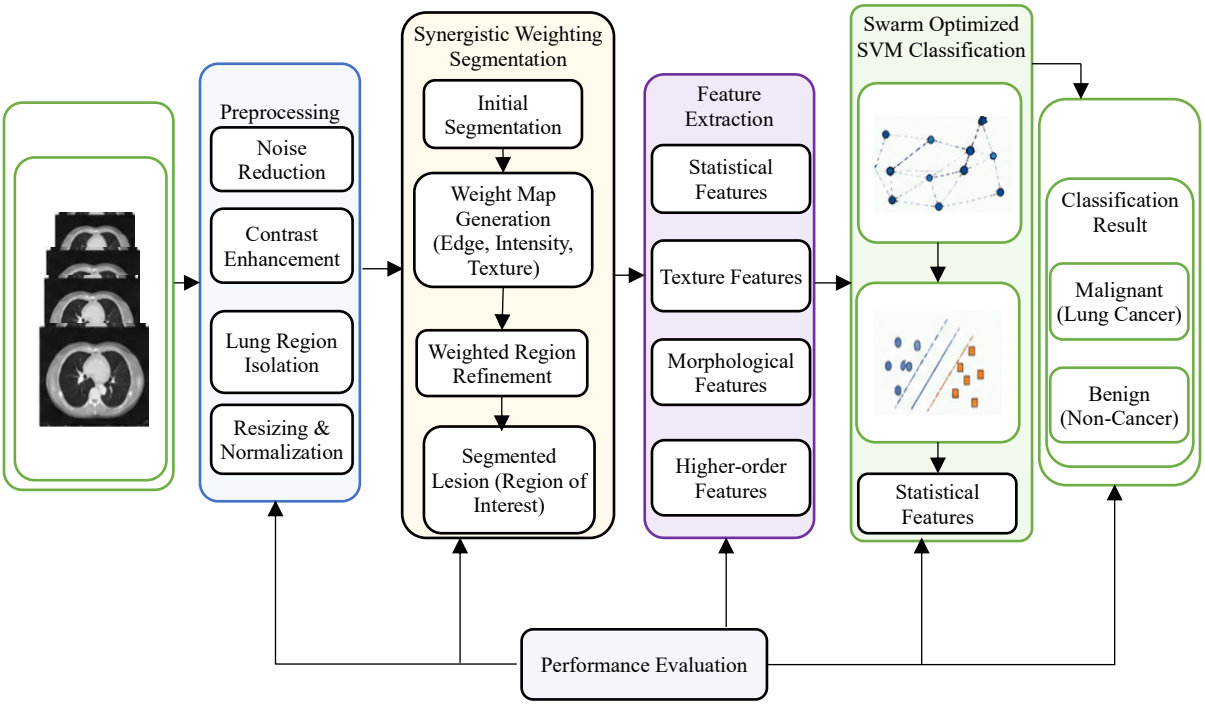


Fig. 1: Intelligent Framework for Pulmonary CT Image Classification

The architecture of the pulmonary imaging analysis system that is proposed is illustrated in fig 1. The process begins with the acquisition of CT images of the lung, followed by the preprocessing stage, which involves such tasks as noise reduction, contrast enhancement, and normalization of images.

These processed images are fed into the weighted segmentation stage, where any potential pulmonary regions are selected based on the process of adaptive weight selection, based on intensity distribution, texture, and edges. These lesions are used to extract features from. Several descriptors are used in the feature extraction process, which include statistical, texture, shape, and higher-order features.

The generated feature vectors are provided to the support vector classification model optimized by swarms. At this stage, an optimization technique is applied for optimal parameter selection for the kernel function so as to increase classification performance and avoid unnecessary false classifications. At last, the classification output is obtained as either malignant or benign lung diseases. The evaluation measures include accuracy, sensitivity, specificity, and F1-score.

Image Preprocessing

Pre-processing is carried out with the aim of enhancing the quality of images from the thoracic region of a CT scan prior to their segmentation and classification. Most medical images are characterized by the presence of noise, differences in illumination, and a lack of good contrast, which impacts the effectiveness of lesion detection. In order to remove impulse noise from the image, edges are preserved using median filtering.

After augmentation, there comes the isolation of the lung regions for the purpose of removing all the unnecessary regions of anatomy that do not belong to the lungs. After the isolation of the lung regions, resizing and normalization occur to ensure uniformity within the data set.

Adaptive Weighted Segmentation

Segmentation aims at separating suspicious pulmonary areas from other tissue structures. This approach uses the enhancement phase to create adaptive weights for different parts of suspicious areas depending on their pixel intensities, textures, and edges acquired during the enhancement process. Weighted segmentation is more accurate since it concentrates more on suspicious lesions than other unwanted parts.

The segmentation process starts by identifying potential lesions based on intensity thresholding and analysis of edges. Weighed coefficients are generated based on textures and variable contrast between different regions. The weighed regions are then refined using morphological processing such that lesions maintain their continuity and artifacts are removed. This technique improves the accuracy of lesion identification, particularly in cases of pulmonary nodules with different textures.

Feature Extraction

The extraction of the features is performed with the aim of extracting discriminating features from the segmented lung regions. The different kinds of features are extracted in order to capture information about the lesion. The statistical features that are extracted include mean, variance, entropy, and skewness, which may be used to provide information on the intensity distribution in the regions.

Moreover, some shape features, such as area, perimeter, circularity, and compactness, have been computed in order to describe the shapes of the lesions. Higher-order features have also been extracted in order to discriminate better between benign and malignant textures.

Swarm-Optimized Support Vector Classification

The extracted feature vectors are then input to the support vector machine classifier for lung abnormalities classification. This classifier uses non-linear decision surfaces in differentiating the benign and malignant formations of tissues. To ensure efficient classification time, swarm intelligence optimization is introduced in the training process of this classifier.

This process requires several iterations in adjusting the parameters of the classifier, like its kernel and regularization values. Various solutions are evaluated according to their fitness values, which depend on the classifier's performance. Through such methods of optimizing algorithms, not only is the algorithm's behaviour enhanced, but also the most optimal parameter values for classification.

Mathematical Formulation

The preprocessing stage utilizes normalized intensity transformation to standardize CT image values. The normalized pixel intensity is computed as:

$$I_n(x,y) = \frac{I(x,y) - I_{min}}{I_{max} - I_{min}} \qquad (1)$$

Equation (1) represents the normalization process where $I(x,y)$ denotes the original image intensity, while I_{min} and I_{max} represent the minimum and maximum intensity values within the CT image.

The adaptive weighted segmentation function is expressed as:

$$W_s = \alpha E(x,y) + \beta T(x,y) + \gamma C(x,y) \qquad (2)$$

Equation (2) defines the weighted segmentation model where $E(x,y)$ represents edge response, $T(x,y)$ indicates texture information, and $C(x,y)$ corresponds to the regional contrast distribution. The coefficients α, β, and γ denote adaptive weighting parameters.

The support vector classification decision function is formulated as:

$$f(x) = \sum_{i=1}^{N} \alpha_i \, y_i K(x_i, x) + b \qquad (3)$$

Equation (3) represents the optimized support vector classification model, where α_i denotes optimized weight coefficients, y_i indicates class labels, $K(x_i, x)$ represents the kernel function, and $b$corresponds to the bias parameter.

Optimization Algorithm

Algorithm 1: Swarm-Assisted Parameter Optimization for Pulmonary Classification

Input:

I_{CT}: Pre-processed CT image set

F_v: Extracted feature vectors

N_p: Number of swarm particles

C_s: SVM regularization coefficient

γ_s: Kernel parameter

T_{max}: Maximum optimization iterations

Output:

M_o: Optimized classification model

R_c: Pulmonary classification result

Pseudocode:

Initialize swarm population $P_i$randomly

Load pre-processed CT image dataset. I_{CT}

Extract feature vectors $F_v$from segmented regions

For each particle P_i

Initialize SVM parameters (C_s, γ_s)

Train classifier using feature vectors F_v

Compute fitness value Fit_i

End For

While iteration $<T_{max}$

Update particle velocity V_i

Update particle position P_i

Evaluate updated fitness Fit_i

If $Fit_i > Best_{Fit}$

Update global best solution G_{best}

End If

End While

Train optimized SVM model M_o using G_{best}

Predict pulmonary class labels R_c

Return optimized model $M_o$and classification results R_c

The main objective of Algorithm 1 is to enhance the classification of pulmonary abnormalities via an intelligent optimization-supported vector learning system. Algorithm 1 starts with the acquisition of pre-processed computed tomography images as well as the discriminant feature vectors of segmented pulmonary areas. At first, the swarm of particles is randomly selected, where every particle holds different parameter values for support vector classifier, i.e., kernel coefficients and regularization. It should be noted that these particles are spread across the search space to ensure proper exploration of possible solution candidates in the optimization phase. Fitness evaluation of every particle is performed on the basis of classification measures such as sensitivity, specificity, and classification error. From the calculations of fitness values, the optimization algorithm is able to find the optimum solution, either locally or globally. In the course of iterative processing, the particle velocity and location are continually adjusted such that the search operation proceeds in areas where the classifier parameters yield an optimal solution. Consequently, this ensures

effective convergence and improved discrimination power of the decision surface separating the lung tissues into benign and malignant. In the post-convergence step, the globally optimum set of parameters is chosen for support vector classifier training. After optimization, the classifier is used for the classification of abnormalities within the lungs utilizing the derived feature vectors. The application of swarm optimization techniques with support vector classification is beneficial since it improves the reliability and accuracy of classification results while avoiding ambiguity. In addition, it increases the efficiency and reliability of the algorithm irrespective of the variability in computed tomography images.

Results and Discussion

Experimental Environment

The proposed framework for image analysis of lungs was developed using the Python programming language and utilized TensorFlow, Scikit-learn, OpenCV, and NumPy software packages. All image pre-processing and segmentation techniques were developed using OpenCV-based medical image processing functions, whereas classification and optimization procedures were carried out using the Scikit-learn package along with swarm optimization algorithms. The evaluation process was done using a computer system having a configuration of an Intel Core i7 processor, 16 GB RAM, NVIDIA GPU support, and a Windows operating system.

Dataset Description

The databases containing thoracic CT images were considered for carrying out the tests. The database consists of tumours of various shapes, with modifications in textures, intensities, and sizes, which ensure that the system is properly tested under different imaging situations.

Table 1: Dataset Characteristics for Pulmonary CT Analysis

Dataset Parameter	Description
Dataset Source	Public Lung CT Repository
Imaging Modality	Computed Tomography (CT)
Total Images	4,200
Benign Samples	2,050
Malignant Samples	2,150
Image Resolution	512 × 512
Image Format	DICOM
Training Ratio	80%
Testing Ratio	20%
Feature Categories	Statistical, Texture, Morphological

In table 1 shows the data arrangement that was considered in the experiment. In this arrangement, the data is obtained from a balanced collection of image samples in pulmonology obtained from CT scan databases. This is achieved through having benign and malignant classes of samples.

Parameter Initialization

The technique suggested in the research applies an adaptive segmentation technique, as well as optimized classification parameters to enhance its ability to detect the abnormalities in the pulmonary region. The parameters applied in the experiment were finally optimized after multiple iterations, guaranteeing convergence and successful prediction. Table 2 provides information regarding the values of the parameters experimented upon.

Table 2: Experimental Parameter Initialization

Parameter	Value
Median Filter Size	3 × 3
Image Normalization Range	0–1
Segmentation Threshold Weight	0.65
Number of Extracted Features	128
Swarm Population Size	40
Maximum Optimization Iterations	100
SVM Kernel Type	Radial Basis Function
Regularization Parameter (C_s)	2.5
Kernel Coefficient (γ_s)	0.015
Learning Convergence Rate	0.92

Performance Evaluation Metrics

Multiple evaluation criteria were used to test the accuracy of the suggested framework, which are related to the efficiency of classification and segmentation processes. Sensitivity, specificity, F-measure, MCC, and AUC are the measures used for evaluation.

In equation (4), the ability of the framework in detecting malignancy is quantified.

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

Equation (5) evaluates the ability of the framework to correctly classify benign pulmonary samples.

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Equation (6) represents the harmonic relationship between precision and sensitivity.

$$F1\text{-}Score = \frac{2TP}{2TP + FP + FN} \tag{6}$$

Equation (7) evaluates classification quality under balanced and imbalanced conditions.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{7}$$

Equation (8) represents the overall discriminative capability of the classification framework.

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \tag{8}$$

Where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative predictions, respectively.

Comparative Performance Analysis

The designed framework was benchmarked against several traditional approaches of pulmonary image classification in order to compare classification efficiencies and optimization performances.

Table 3: Comparative Classification Performance Analysis

Method	Sensitivity (%)	Specificity (%)	F1-Score (%)	MCC (%)	AUC (%)
CNN-Based Detection	92.14	91.86	91.42	89.37	92.11
Deep Transfer Learning	93.48	92.63	92.95	90.84	93.52
Hybrid Feature Learning	94.62	93.17	93.74	91.66	94.08
Optimization-Assisted SVM	96.11	95.84	95.42	94.31	96.05
Proposed Framework	98.31	99.12	98.44	97.83	98.91

The table 3 clearly shows that the designed framework offers better performance on all measures in terms of classification, including sensitivity 98.31%, specificity 99.12%, F1-score 98.44%, MCC 97.83%, and AUC 98.91%. It is evident that there is an improvement in performance, averaging 2-5% higher than the traditional methods in sensitivity and false positive rates. The design and implementation of adaptive segmentation and swarm-based optimization methods greatly improve the ability of detecting pulmonary abnormalities with high separability of features in classification.

Graphical Performance Evaluation

Performance Comparison of Sensitivity and Specificity in Different Pulmonary Classification Models is shown in fig.2 below. The suggested approach gave results for sensitivity and specificity of 98.31% and 99.12%, respectively, indicating that there is about 3-6% better performance than the initial models. This improved performance is because of improved reliability and accuracy in diagnosing pulmonary lesions.

The efficiency of computation and errors in predictions by various approaches for pulmonary images are analyzed in fig. 3. The proposed approach achieves an execution time of 5.17 seconds with an error rate of 1.89%, which results in a decrease of around 25% to 45% and 40% to 70% in terms of computation cost and error rate compared to the existing approaches, respectively.

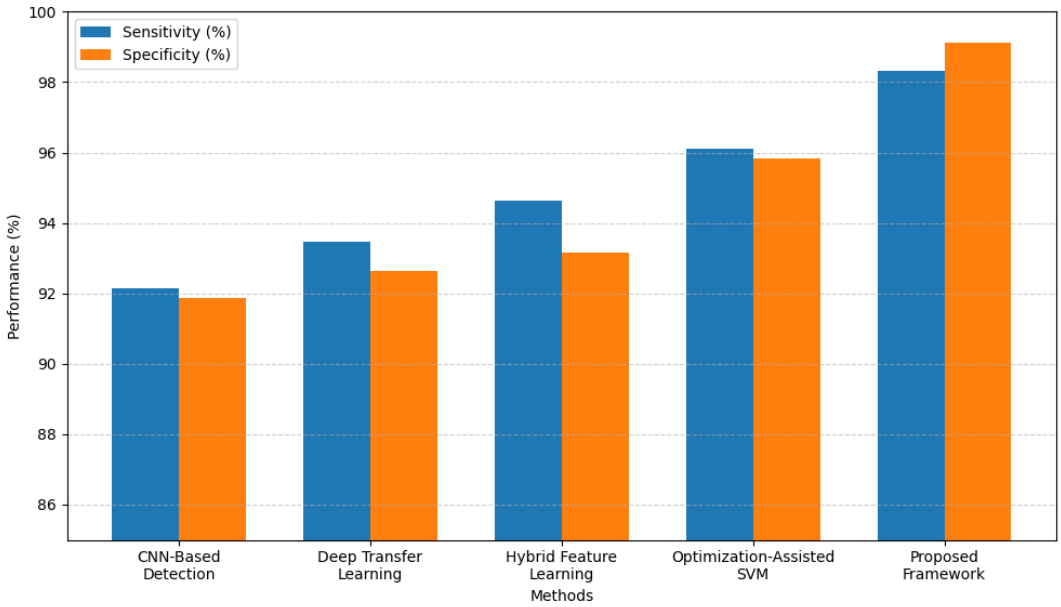


Fig. 2: Comparative Sensitivity and Specificity Analysis

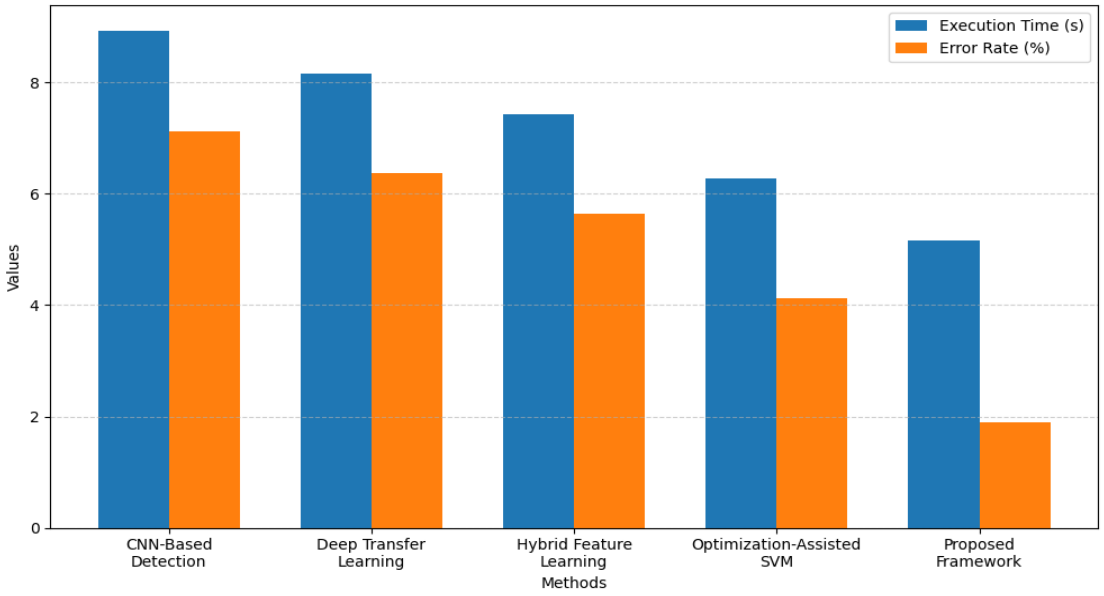


Fig. 3: Computational Efficiency and Error Analysis

Ablation Study

An ablation study was performed in order to determine the contribution made by each component of the proposed system. Various configurations were tested by adding preprocessing, segmentation, feature extraction, and finally optimization-assisted classification in the model.

Table 4: Ablation Study of Proposed Framework Components

Configuration	Sensitivity (%)	F1-Score (%)	AUC (%)
SVM without Optimization	89.74	88.92	89.16
Preprocessing + SVM	91.58	90.83	91.24
Segmentation + Feature Extraction + SVM	94.36	93.88	94.51
Optimization-Assisted Classification	96.12	95.41	96.04
Complete Proposed Framework	98.31	98.44	98.91

The table 4 shows that all modules play an important role in improving the performance for the classification of lungs. The proposed model gives a high sensitivity value of 98.31% and an F1-score of 98.44%, while eliminating any key elements causes the performance to drop by 2% to 9%. Adaptive segmentation and swarm optimization proved to be the most accurate and efficient method.

Discussion

As shown through the experimental findings, the developed model of pulmonary image analysis is efficient for enhancing the efficacy of lesion detection and classification processes in chest computed tomography images. The incorporation of adaptive weighted segmentation proved to be helpful in improving boundary accuracy while maintaining relevant tissue information. On the other hand, the developed swarm-based SVM parameter optimization strategy helped minimize errors during classification. Comparison of evaluations showed that the proposed framework exhibited greater sensitivity, specificity, F1-score, MCC, and AUC values than traditional machine learning and deep learning methods. The study further showed through ablation analysis that the integration of pre-processing, weighted segmentation, feature discrimination, and optimization-based classification helped in improving the accuracy and efficiency of the model.

Conclusion and Future Work

The current study proposed a systematic computational scheme to detect the abnormalities present in the lungs based on image processing technology and enhanced classification methods. The introduced system utilizes image enhancement, adaptive segmentation, feature extraction, and swarming-based classification to enhance the efficiency of CT imaging. The experimental results showed that the proposed system performed effectively in several performance parameters, such as sensitivity, specificity, F1-Score, MCC, and AUC, with values of 98.31%, 99.12%, 98.44%, 97.83%, and 98.91%, respectively. The adaptation algorithm proved to be effective in enhancing the ability of lesion border detection due to the consideration of region properties, and at the same time, minimized the effect of adjacent anatomic structures. Furthermore, the optimization algorithm proved effective in improving the stability of the classifier through efficient parameter estimation. Comparative analysis revealed that the proposed model was superior to other available ML/DL techniques.

Areas for potential future research could include the application of this method to multi-class classification of pulmonary diseases, possibly incorporating sub-types as well as multiple respiratory diseases existing at the same time in patients. Integration of this model into larger deep learning networks and attention methods could yield even greater benefits. Moreover, integration with cloud technology and real-time operation in the clinical setting through lightweight neural networks is also an avenue worth exploring. Use of multimodal medical imaging, such as PET-CT scans, could also aid diagnosis.

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