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LUNG CANCER DETECTION USING RESNET50-CNN MODEL IN IMAGE PROCESSING

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Abstract

Lung cancer poses a major public health concern, leading to the deaths of around one million people worldwide every year. Due to prevailing clinical cases, identifying lung cancer on chest CT scans has become crucial. Despite the necessity for accurate detection, automated testing systems fall short, and lung cancer screenings remain costly. Furthermore, utilizing numerous complex data sets in clinical settings demands substantial time and expertise. Nevertheless, dealing with the extensive and rapidly expanding cancer-related databases presents challenges in analysis, resulting in a lack of accuracy. To address this issue, we introduced a Resnet-50 Convolutional Neural Network (ResNet50-CNN) technique to enhance the accuracy of classifying lung cancer or non-cancer images. We preprocess lung cancer images using the Gaussian Mixture Model (GMM) to maximize the distance between the object and the background. We analyze the global best position and select features using an Enhanced Particle Swarm Optimization (PSO) algorithm. The proposed ResNet50-CNN model using a Deep Learning (DL) algorithm can accurately distinguish lung cancer images from non-cancer images. Furthermore, the performance evaluation of the proposed method can be analyzed in terms of accuracy, F1 score, sensitivity, and specificity. Moreover, when comparing the proposed ResNet50-CNN technique with previous methods, the accuracy is enhanced to 95.6%.

Keywords: Lung cancer, Image processing, DL, ResNet50-CNN, GMM, feature selection, and CT image dataset,

1. INTRODUCTION

Lung cancer affects both men and women and accounts for approximately 25% of cancer-related deaths, making it the deadliest malignancy worldwide. Medical professionals rely on histopathology images of biopsy tissue from affected lung areas to diagnose the disease. Furthermore, different tests are conducted to identify cancer cells and imaging tools such as X-rays and CT scans are utilized to eliminate other potential causes. Additionally, a skilled pathologist reviews the microscopic histopathology slides, conducts a biopsy for confirmation of the diagnosis [1-2], and defines lung cancer types and subtypes. Non-small cell lung cancer and non-small cell lung cancer are the two main forms of the disease. Since smoking increases the risk of disease, early identification is crucial to save lives. Lung cancer cells can spread to other body areas if not detected early. Lowering lung cancer mortality using low-dose computed tomography (LDCT) screening is a successful strategy.

Furthermore, symptoms of lung cancer can consist of voice alterations, coughing, chest discomfort, wheezing, and other discomforting signs [3]. The advancement of Computer-Aided Diagnosis (CAD) has shown encouraging outcomes in medical image interpretation in recent years. Deep learning (DL) methods, notably transfer learning, have proven to be effective tools for enhancing pre-existing models and optimizing the efficacy of DL models.

The lung imaging database consortium is creating an accessible online image database to serve as a global research resource. Compile a database to guide CAD procedures using CT scans to assess lung cancer stages. Additionally, the database was developed to help identify and classify pulmonary nodules, combining geographic and temporal data with the effectiveness of CAD technology. In addition, they perform analysis for subsequent processing during image processing by improving image clarity through edges, boundaries, and brightness. Therefore, [4] these frequency responses or spatial multiplexing techniques are used for image enhancement.

By providing timely and efficient care, early diagnosis of pulmonary abnormalities is essential to lowering the risk. Manual diagnosis of pneumonia is difficult, prone to subjective discrepancies, and may result in treatment delays. In addition, areas of pneumonia may be obscured by x-ray scans. Since it is difficult to detect abnormalities with X-rays, its evaluation accuracy is significantly lower than other diagnostic approaches. Therefore, there is a need to promote effective DL methods that provide substantial accuracy in image classification efforts [5].

Even though CT scans are the best imaging technology available to medical professionals, it can be challenging for medical professionals to analyze and detect cancer from these scans. Furthermore, the risk and death rate of the illness might be decreased with early diagnosis and treatment. [6] However, variations in CT scan intensity and inaccurate anatomical assessments made by radiologists and medical specialists might make it difficult to identify cancer cells.

The contribution of this paper is to analyze lung cancer features using the Chest CT-Scan images database originally collected from Kaggle. Furthermore, it presents a method for preprocessing lung cancer images using GMM to increase the distance between the object and the background. It also introduces the EPSO algorithm for estimating the optimal global position for feature selection. Additionally, the paper proposes a ResNet50-CNN model to improve the accuracy of predicting lung cancer and non-cancer images using the DL algorithm. Finally, the method is capable of analyzing lung images through performance evaluation.

1.1 Lung Cancer

In recent years, lung cancer deaths have decreased significantly, primarily due to improvements in treatment options. These treatments include various methods, including surgery, chemotherapy, immunotherapy, radiation therapy, and targeted drug therapy. Lung cancer is defined by uncontrolled cell division in the lungs due to mutations in the normal cell replication process. When these mutated cells multiply, they lead to the development of lung cancer. Various treatment approach’s purpose to target and combat these abnormal cells and improve outcomes for those analyzed with the disease.

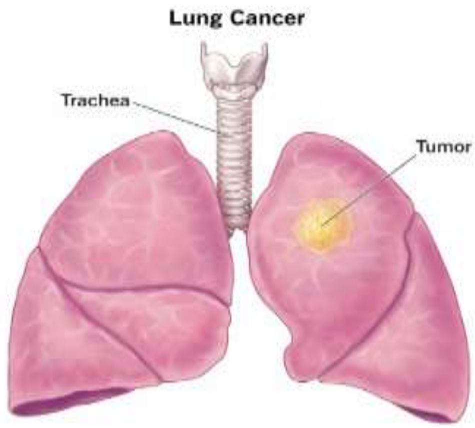


Figure 1. Lung Cancer Diagram

As shown in the lung cancer diagram in figure 1, alveoli begin in the lungs' bronchioles or small air sacs within the alveoli.

1.2. Lung Cancer Types

Although the lungs can be affected by many different types of cancer, "lung cancer" often refers to both small cell and non-small cell lung cancer.

A. Non-Small Cell Lung Cancer (NSCLC)

More than 80% of instances of lung cancer are non-small cell lung cancer, making it the most prevalent kind of the disease. The two most pervasive subtypes of non-small cell lung cancer are adenocarcinoma and squamous cell carcinoma. The less common NSCLC subtypes adenosquamous carcinoma and sarcomatoid carcinoma are also present.

B. Small cell lung cancer (SCLC)

Small cell lung cancer is harder to treat because it grows faster than non-small. It is usually considered a small lung tumor that spreads to other body parts. In addition, a specific type of SCLC consists of a small cell cancer known as oat cell carcinoma.

1.3 Symptoms of Lung Cancer

Most lung cancer symptoms are similar to those of other less serious diseases. In addition, lung cancer may not show symptoms until late in the disease, although early signs are analyzed.

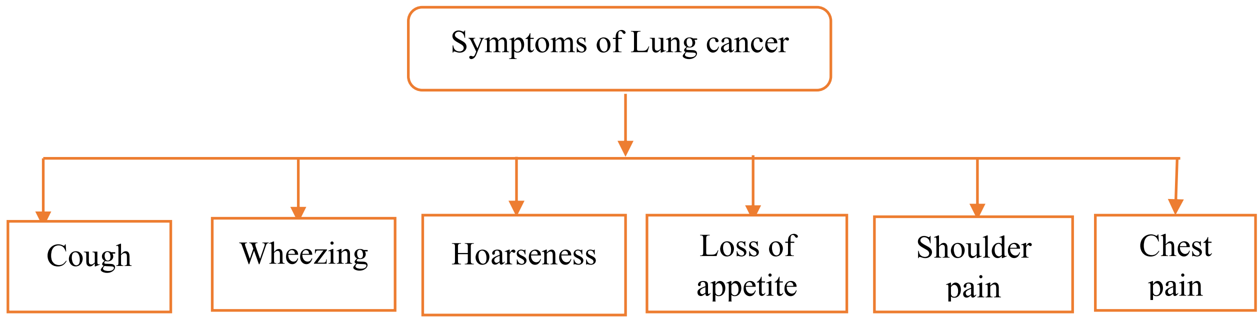


Figure 2. The Structure of Lung Cancer Symptoms

Certain patterns can help identify possible signs of lung cancer, such as a persistent cough that doesn't worsen over time. As shown in figure 2, common symptoms include dyspnea, tachypnea, and superior vena cava syndrome. Early diagnosis and timely medical intervention are critical to manage the condition effectively.

1.4 Analyzing Computed Tomography Images Using Deep Learning

Computed tomography imaging can be used to create detailed pictures of the human body to diagnose and monitor diseases such as cancer, heart disease, and trauma. The integration of CT imaging in modern medicine equips experts with precise tools for visualizing internal organs, aiding in informed diagnosis and treatment. Additionally, CT scans offer in-depth body imaging data, enabling the detection of abnormalities beyond traditional techniques. Leveraging deep learning in CT image processing presents numerous benefits. Different CT image datasets with varying resolutions, noise levels, and features can be produced by DL algorithms, capable of processing a broad range of input data. This enables real-time CT image analysis and enhances procedural efficiency.

2. LITERATURE SURVEY

The offered an overview of advancements in lung cancer detection methods and CT imaging. Furthermore [7], image processing methods employed for preprocessing can be examined for noise reduction, improvement, and segmentation. One of the most dangerous cancers that seriously endanger people's health is lung cancer. Although histology is the gold standard for staging and classifying lung cancer, novice clinicians can find it challenging to analyse broad histopathology images. [8]. Clinical image analysis of lung cancer utilizing the DL algorithm aims to compare various techniques based on their performance, advantages, and limitations. Additionally, it provides insight into approaches to lung cancer analysis and classification [9]. Moreover, discussed various limitations in adapting current DL-based models for the automated identification of cancer patients through pre-trained models [10].

Numerous technological stages must be performed to enhance the functionality of medical tests because image processing is necessary for computer vision and medical image processing [11]. Th novel [12] suggest an advanced Machine Learning (ML) model that uses CT scan pictures to stage lung cancer and offers a reliable diagnosis tool. However, traditional diagnostic methods often lead to over-interpretation and vague interpretation when analyzing early detection and measurement. The [13] novel Biomedical Image Analysis for Colon and Lung

Cancer Detection using Tuna Swarm Algorithm with DL (BICLCD-TSADL) model. The BICLCD-TSADL method identifies and classifies colon and lung cancers by analyzing biomedical images.

This study [14] optimized the existing pre-trained CNN method for detecting lung cancer using the most effective optimization techniques with histopathology images. Additionally, the model was evaluated on the LC25000 histopathology image dataset to assess CNN performance. Feature extraction in image acquisition, thresholding, and image preprocessing using Deep Neural Network (DNN) technology for lung cancer detection. Furthermore, it was demonstrated that lung CT image segmentation techniques can extract specific features [15]. Although employing Convolutional Auto Encoder (CAE) models to analyze histopathology images has improved lung and colon cancer detection and prognostic assessment, diagnosing these cancers from histopathological images still presents a challenging task in clinical diagnosis [16].

Table 1. Deep Learning for the Identification of Lung Cancer

Author	Year	Technique	Limitation	Lung Cancer Image
Naseer, S [17]	2023	AlexNet-SVM	Automation has an impact on the effectiveness of cancer excision techniques when malignancies are connected to other organs.	CT scan images
R. Mahum [18]	2023	Lung-RetinaNet	Early diagnosis of lung cancer remains a challenge.	CT scan
S. Oh [19]	2021	EfficientNet, and ResNet	A thorough analysis of different clinical factors is necessary to diagnose lung cancer.	Positron Emission Tomography (PET)
W. Cao [20]	2020	CNN	Pulmonary nodular lesions are often asymptomatic, making diagnosis very difficult.	Low-Dose Computed Tomography (LDCT)
Y. Xie [21]	2019	ResNet-50	Detecting malignant nodules is challenged by the absence of large-scale datasets for training.	CT images
Li, Y [22]	2021	DNN	Determining the prognosis of lung cancer with low values in positive specimens is a difficult task.	Lung image
W. Shao [23]	2020	Ordinal Multi-Modal Feature Selection (OMMFS)	Combining histopathology images with single-gene data approaches has its limitations.	Histopathological Images
Lakshmanaprabu S.K [24]	2019	Optimal Deep Neural Network (ODNN)	Early detection of cancer increases survival rates	CT Image
H. Guo [25]	2020	CNN	All-cause mortality risk in a population is complex to predict	Chest Radiographs (X-ray)
Song [26]	2022	Faster R-CNN	Locating and analyzing CT images can be difficult due to their varying locations and intensities.	CT Image

Nasrullah N [27]	2019	Gradient Boosting Machine (GBM)	Early diagnosis of lung cancer is a significant challenge for survival.	Chest X-ray
Venkatesh, C [28]	2024	CNN	In rare cases, benign tumours in the lungs can be life-threatening.	CT image

Table 1 describes the analysis of lung cancer images using DL techniques derived from previous methods and their limitations.

The author proposed a Rider Optimization Algorithm (ROA) based on reinforcement ML to predict lung and colorectal cancer. Furthermore, it is indicated that the classification consequences are significantly improved on the LC25000 dataset [29].

Table 2. Lung Cancer Based on Image Processing Using Machine Learning

Author/Ref No	Year of Publication	Dataset	Classification	Accuracy
Raza, R [30]	2023	IQ-OTH/NCCD	EfficientNet	93.6%
N. Kumar [31]	2022	LC 25000	Multilayer Perceptron (MLP)	91.06%
A. H. Chehade [32]	2022	LC 25000	XGBoost, LightGBM	92%
S. Tummala [33]	2023	LC25000 histopathology images	EffcientNetV2	92.3%
Salama, W.M [34]	2022	CXR lung images	ResNet50	93.4%
Sim Y [35]	2019	Chest CT scan	DCNN	95%
Said, Y [36]	2023	Decathlon lung dataset	Self-Supervised Neural Network	93.7%
Xu Y [37]	2019	Non-Small Cell Lung Cancer	Recurrent Neural Networks (RNN), CNN	91.4%
Sethy PK [38]	2023	LC2500	Discrete Wavelet Transform (DWT), AlexNet	93%
Jamshidi [39]	2024	CT scan image	Multi-Layer Perceptron (MLP)	94.6%

As shown in table 2, image dataset classification techniques using ML to analyze lung cancer based on image processing can improve its accuracy by accessing reference years of previous publications.

The CNN method proposed by [40] analyses advanced performance measures based on CT scan images and histopathology images. While several transformation methods can effectively reduce features to enhance data representation, the need for significant computing power and resources could potentially harm the well-being of lung cancer patients [41]. A highly random tree classifier and a pre-trained VGG16 model were utilized as the feature extraction and selector in the suggested framework [42]. Performance was assessed using fuzzy metrics such as F1 score, sensitivity, and precision.

Table 3. Lung Cancer Based on Feature Selection and Classification Method

Author	Year	Feature Selection	Classification	Performance Evaluation	Achieved Accuracy
M. Mohsin [43]	2020	wrapper-based feature selection	Adam-Cuckoo Search-Based Deep Belief Network (Adam-CS-based DBN)	Specificity, Sensitivity	90%
Gudur, A. [44]	2023	Ant Colony Optimization (ACO)	SVM	AUC-ROC, Accuracy	92.14%

Wang, Y [45]	2023	Weight-Based Feature Selection (WBFS)	Bayesian Network (BN)	Accuracy	87.5%
Dr. P [46]	2022	Contrast Limited AHE (CLAHE)	SVM, ANN	Sensitivity, Specificity	88%
Morgado, J [47]	2021	Region Of Interest (ROI)	Extreme Gradient Boosting (XGBoost) and Logistic Regression (LR)	Area Under the Curve (AUC)	73%
Omar Abdelwahab [48]	2022	Recursive Feature Elimination (RFE)	SVM, RF	False Positive Rate (FPR)	91%
Liangyu Li [49]	2024	Gray-level co-occurrence matrix (GLCM)	SVM, Radial Base Function (RBF)	FPR, Accuracy, sensitivity, specificity	93.2%
Teresa Kwamboka Abuya [50]	2024	Grey Wolf Optimization Algorithm (GWOA)	CNN	FPR	0.023%
Mahto, R [51]	2023	Cuckoo Search Spider Monkey Optimization (CSSMO)	Minimum Redundancy Maximum Relevance	Precision, F1-Score	90.7%
Negar Maleki [52]	2023	Genetic Algorithm (GA)	Gradient Boosting (GB), RF, and SVM	Accuracy	94.9%
Michael Mary Adline Priya [53]	2020	Whale Optimization-Based Feature Selection Technique	K-Nearest Neighbour (KNN)	Recall	90.3%

As indicated in table 3, the performance evaluation using the feature selection and classification techniques derived from previous methods can predict lung cancer with improved accuracy.

Using lung images directly as input images and performing experiments on LDNNET with other combined parameter settings can improve both dataset's accuracy to 94.9% [54]. In addition, the hyperparameters of the CNN model facilitate an automatic lung nodule detection method that leverages transfer learning to optimize the optimizer, block size, and number of epochs [55].

3. PROPOSED METHODOLOGY

In this section, a dataset of chest CT scan images from Kaggle can be used to improve the accuracy of lung cancer diagnosis. The GMM model can also be examined for image preprocessing to enhance subject-background separation. Moreover, the EPSO algorithm can assess the global best position for precise feature selection in cancer images. Finally, the proposed ResNet50-CNN model can classify lung cancer images into cancerous and non-cancerous categories and has shown significant performance improvements in assessing lung cancer images.

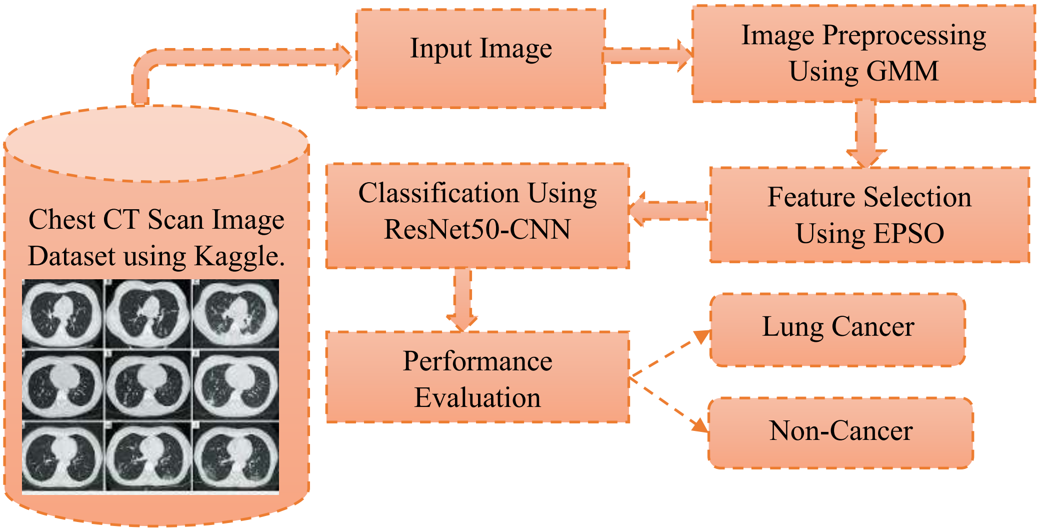
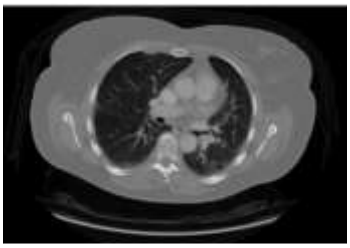


Figure 3. The Proposed Resnet50-CNN Technique Based Architecture Diagram

Using the ResNet50-CNN technology-based feature map, the proposed ResNet50-CNN model has enhanced the accuracy of classifying lung cancer images into cancer and non-cancer categories, as depicted in figure 3. The development of the ResNet50-CNN technique has significantly improved the performance evaluation of lung cancer images. The findings indicate that this proposed medical image processing method could enhance lung cancer diagnosis and treatment.

3.1 Dataset Collection

This section shows that the method proposed can improve accuracy employing a dataset of chest CT scan images collected from Kaggle. In addition, they analyzed 1,000 lung images from the chest CT scan image dataset into three dissimilar files (Training – 708, Testing – 292, and Validation). The data collection can be divided into three categories (70%, 20%, and 10%): training, testing, and validation sets to improve accuracy. The website https://www.kaggle.com/datasets/mohamedhanyyy/chest-ctscan-images can be used to analyze the lung cancer dataset.



(a) Test

(b) Train

(c)Validation

Figure 4. Dataset Lung Cancer CT Image Collection

Figure 4 illustrates that training, testing, and verifying the lung cancer CT scans gathered from the dataset can increase accuracy.

3.2 Gaussian Mixture Model (GMM)

In this section, images can be preprocessed using a Gaussian mixture model to maximize the distance between the subject and the background. Lung images are obtained using the GMM method, which analyzes clusters of pixels in the image as a multivariate Gaussian distribution. In addition, the Bhattacharya metric, which uses multiple metrics to calculate distance, provides better results than similar metrics. Additionally, lung cancer images can be analyzed using metric metrics and a simple analysis design. Thus, Bhattacharya distance can be used to measure differences between distributions using the GMM method.

As illustrated in Equation 1 and 2, Gaussian mixture models can be utilized to estimate the mean and covariance matrices of high-dimensional random vectors by summing the densities of the density-weighted components. Let's assume $\vec{m}$ −Dimension random vector,$j_a(m)$ −component densities, $\vec{\mu}_a$ −mean vector, $\sum_a$ −coverence matrix, F-Variate Gaussian function.

$$U(\vec{m}|\lambda) = \sum_{a=1}^{x} U_a j_a(\vec{m}) \tag{1}$$

$$j_a(m) = \frac{1}{(2\pi)^{F/2} |\sum_a|^{1/2}} exp\left\{-\frac{1}{2}(\vec{m} - \vec{\mu}_a)' \sum_a^{-1}(\vec{m} - \vec{\mu}_a)\right\} \tag{2}$$

As shown in equations 3 to 4, calculate the distance between the object and background distributions using the mean and distribution variance. Let's assume μ_O −mean object, $\sum_O$ −varience distribution object, $\mu_J, \sum_J$ −bacground parameter, U-pixel value, A-Image, G-random number, Y-number of images.

$$U(A) = U(A/G_K) + U(A/G_J) \tag{3}$$

$$\begin{gathered} U(A/G_K) \sim Y(\mu_K, \textstyle\sum_K) \\ U(A/G_J) \sim Y(\mu_J, \textstyle\sum_J) \end{gathered} \tag{4}$$

The mean distance between object and background distributions can be estimated based on the distribution variance of pixel value in lung cancer image preprocessing.

3.3 Enhanced Particle Swarm Optimization (EPSO)

In this section, the features can be selected to provide the overall optimum using a modified particle swarm optimization algorithm. Further, these populations are analyzed into clusters, and each point is considered a particle. Particles are initialized randomly in the search space of the objective function. Each particle can be evaluated during a series of iterations between the appropriate state of the population and a stochastic search between the best solutions for the particles. Furthermore, in the EPSO method, each particle can be simultaneously evaluated in the search space, and its velocity is dynamically adjusted based on the experience of particle companions, which corresponds to two properties: velocity vector and position vector.

Algorithm: EPSO

Input: Distance between pixels values U

Output: Global best position R

Start

1. Compute the particle position

2. Initialize the best particle position← W

3. Update the optimal position of the swarm

    For each $d(w) < d(r)$

        Calculate the velocity of the particles

            Compute the maximum iteration value or threshold

                Enhance the particle velocity and position

$$Q_{af}(z+1) = L * Q_{af}(z) + e_1 * g_1 * \left(w_{af}(z) - m_{af}(z)\right) + e_2 * g_2 * \left(w_{rf}(z) - m_{af}(z)\right) \quad (5)$$

$$m_{af}(z+1) = m_{af}(z) + Q_{af}(z+1) \quad (6)$$

Compute the optimal position of particles and swarm

For each $d(m_a) < d(w_a)$

For each $d(w_a) < d(r)$

End for each

End for each

End for each

Evaluate the global best position$\leftarrow R$

Return R

End

The speed of each particle in the search space is assessed as a dynamic parameter that is adjusted to calculate the optimal position of the particles and swarm accurately. By fine-tuning the velocity, the particles can move more efficiently through the search space, leading to improved swarming results. Let's assume $Q_{af}(z+1)$ *and* $m_{af}(z+1)$ −velocity of particle, z-iteration, w_{rf} −paricle global position, *the* $w_{af}(z)$ −best position of the particle, L-weight, e-acceleration coefficients weight, g-random number, d-function, R-global, w-particle.

3.4 ResNet50-Convolutional Neural Network (ResNet50-CNN)

In this section, the RESNET-50-CNN network model is applied to improve the accuracy of classifying lung cancer or non-cancer based on the lung image dataset. ResNet50 utilizes residual connections to combat network mapping issues and alleviate gradient vanishing in DNNs. The ResNet50-CNN architecture comprises 50 layers, encompassing convolutional, pooling, fully connected, and shortcut layers, enhancing the efficacy and adaptability of the pre-trained weight model on the dataset. Moreover, all input neurons are connected to convolutional layers, enabling the analysis of long feature vectors through regularization across multiple convolutional layers. Furthermore, these layers are connected to fully connected networks, allowing for flattened data from previous pooling or convolution steps on lung cancer images to be processed in a fully connected layer.

In the ResNet50 method, the concatenation skips the training of some layers and directly concatenates to the output. The dependence value in the input lung image can be estimated by weighting the layers. Compute the output of the last activation n of the function, as shown in Equation 7. Let's assume m-input, d(m)-activation function S(m)-network layer.

$$\begin{gathered} S(m)=Rd(l_m+j) \\ S(m)=d(m) \end{gathered} \quad (7)$$

Equation 8 evaluates the increased output value of the CNN connected to the network.

$$S(m) = d(m) + m \quad (8)$$

Calculate the feature map values by applying the filter and iterating the same filter on the input as specified in equation 9. Let's assume d-input, R-feature map, x and y- index of row and column matrix, s-kernel, O-kernel convolution, a and b-values,

$$R[x, y] = (d * s)[x, y] = \sum_b \sum_O s[b, O]\, d[x - b, y - O] \quad (9)$$

A schematic solution for filter sizing to calculate the padding width is shown in Equation 10. Let's assume U-padding, d-Filter dimension.

$$U = \frac{d-1}{2} \quad (10)$$

Equation 11 shows that lung cancer can be characterized by analyzing lines and complements and estimating the output matrix's dimensions. Where H-stride, Y_o −output matrix, Y_i −input matrix.

$$Y_o = \left[\frac{Y_i + +2_u d}{H} + 1\right] \quad (11)$$

The dimensional of the output matrix is used to classify lung cancer by applying input filters and value-based weighting layers to calculate feature map values.

4. RESULT AND DISCUSSION

The proposed ResNet50-CNN method for predicting lung cancer can be used as the basis for performance analysis using the chest CT scan image dataset collected from Kaggle. Furthermore, the accuracy of images of lung cancer can be increased by contrasting the suggested method with traditional techniques. Predictions of precision, accuracy, sensitivity, specificity, F1 score, error, mean square error, ROC, DSC, MHD, and IoU are also possible using the DL algorithm-based performance evaluation. In addition, accuracy assesses the ability to identify lung image results with current information features.

4.1 Comparison Result

The accuracy of the ResNet50-CNN method in predicting lung cancer using the breast CT scan image dataset is compared with the previous analysis's AlexNet-SVM, ODNN, and CSSMO techniques.

Table 4. Simulation Parameter

Simulation	Variable
Dataset Name	Chest CT-Scan images Dataset
Total Images	1000
Training	708
Testing	292
Language	Python
Tool	Jupyter

As shown in table 4, the training and testing of whole lung images to implement simulation parameters and evaluate lung cancer images can be identified in a Jupyter notebook based on Python language.

Table 5. Confusion Matrix

Matrices	Equations
Accuracy	$\frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}}$
Sensitivity	$\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$
Specificity	$\frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$
Precision	$\frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$
F1-Score	$\frac{\text{2Truue Positive}}{\text{2Truue Positive} + \text{False Positive} + \text{False Negatitive}}$
Error	$\frac{\text{False Positive} + \text{False Negatitive}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negatitive}}$
Dice Similarity Coefficient (DSC)	$\frac{\text{2Truue Positive}}{\text{2Truue Positive} + \text{False Positive} + \text{False Negatitive}}$
Jaccard Score (Js)	$\frac{\text{DSC}}{2 - \text{DSC}}$
Modified Hausdorff Distance (MHD)	$\frac{1}{N_a}\sum_{a \in A} \min_{b \in B} \|a - b\|$
Intersection Over Union (Iou).	$\frac{\text{Truue Positive}}{\text{Truue Positive} + \text{False Positive} + \text{True Negative}}$

Table 5 illustrates how lung cancer images can be enhanced and analyzed using confusion matrix techniques such as true positive, true negative, false positive, and false negative.

Table 6. Analysis of Performance Evaluation Method

Reference No	Method	Performance Evaluation
17	AlexNet-Support Vector Machine (AlexNet-SVM)	Sensitivity, Specificity
24	ODNN	Accuracy, Specificity
51	Cuckoo Search Spider Monkey Optimization (CSSMO)	Recall, Precision, F1-score

Performance evaluation can be identified through various references and techniques, as demonstrated in Table 6.

Table 7. Comparison Model of Performance

Methods	**SARS-COV-2 Ct-Scan Dataset**			**CT Scan Images for Lung Cancer**			**IQ-OTH/NCCD**			**Chest CT-Scan images Dataset**		
AlexNet-SVM	Tra	Tes	Acc	Tra	Tes	Acc	Tra	Tes	Acc	Tra	Tes	Acc
ODNN	1457	1024	76.3	1489	785	79.2	872	423	80.3	877	123	83.4
CSSMO	1494	987	78.6	1378	896	81.6	941	354	84.6	769	231	87.2
CNN	1699	782	82.4	1530	744	83.2	1,059	236	88.9	822	178	91.6
ResNet50-CNN	1921	569	85.3	1171	1103	86.1	974	321	90.7	853	147	95.7

The lung cancer prediction accuracy by testing and training using the proposed approach and different datasets such as SARS-COV-2 CT scan, IQ-OTH/NCCD, lung cancer CT scan images, and thoracic CT scan images are described in table 7.

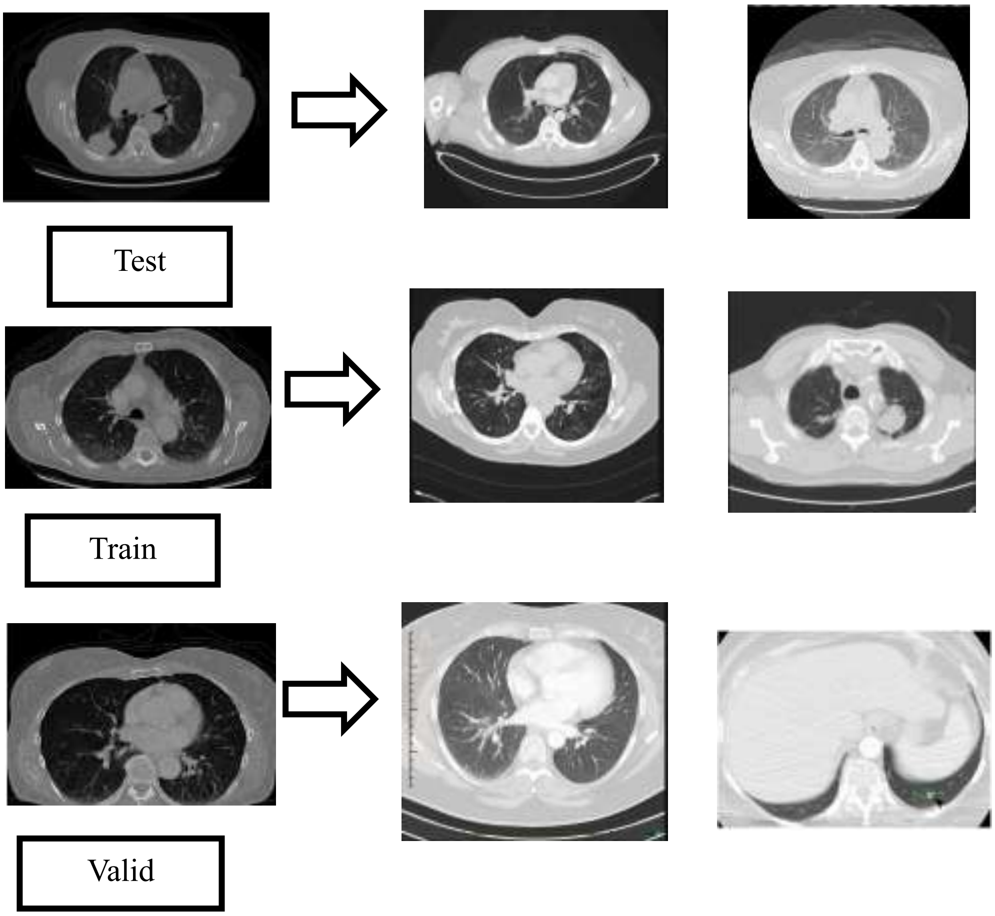


Figure 5. Enhanced Lung Cancer Chest CT-Scan images Dataset

Figure 5 shows that the training, testing, and validation of three image classifiers can be optimized to analyze lung cancer images collected from a dataset of chest CT scan images.

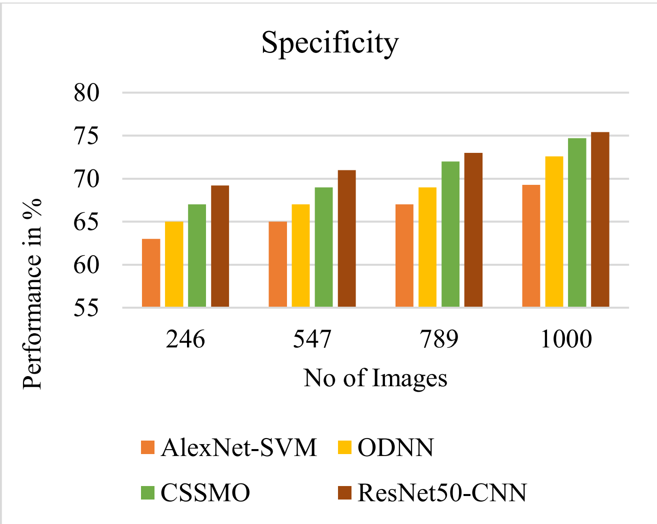


Figure 6. Analysis of Specificity

As demonstrated in Figure 6, the suggested ResNet50-CNN technique can be used to analyze specificity to determine lung cancer image accuracy. Furthermore, the accuracy of the proposed ResNet50-CNN approach improves to 75.4% when compared to previous AlexNet-SVM, ODNN, and CSSMO methods. Analysis of the method specification derived from the last method showed significant improvements of 69.3%, 72.6%, and 74.7% accuracy.

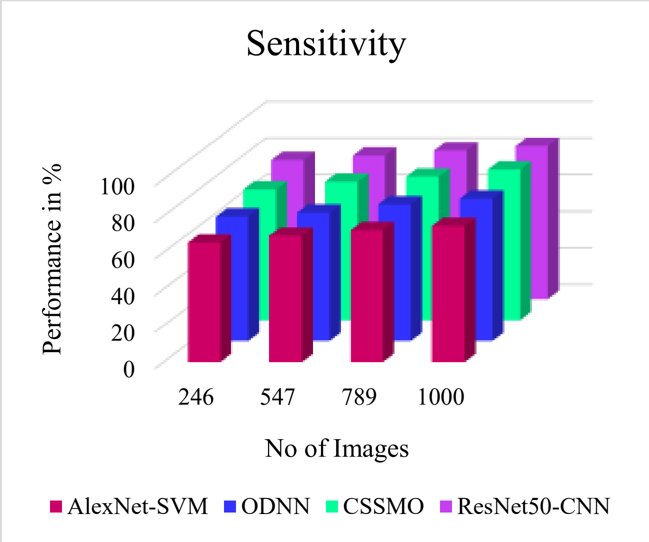


Figure 7. Analysis of Sensitivity

In Figure 7, the accuracy of lung cancer images can be assessed by conducting sensitivity analysis using the presented ResNet50-CNN approach. The accuracy of the proposed ResNet50-CNN method has improved to 83.6% compared to the previous AlexNet-SVM, ODNN, and CSSMO methods. Sensitivity analysis of the method obtained from the last approach shows significantly improved accuracy of 74.6%, 77.9%, and 82.3%, respectively.

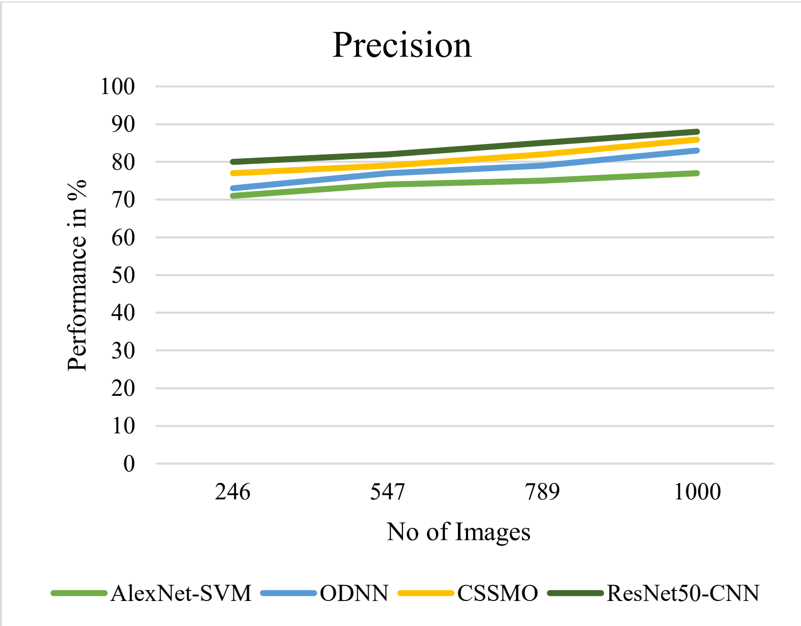


Figure 8. Analysis of Precision

By utilizing the proposed ResNet50-CNN technique for precision analysis, the accuracy of figure 8 lung cancer images can be assessed. The exactness of the proposed ResNet50-CNN technique has increased to 88.2%, exceeding the accuracy of previous methods. Achieving a significant improvement over previous methods like ODNN and CSSMO (77%, 83%, and 85.9%), AlexNet-SVM provides accurate analysis identification.

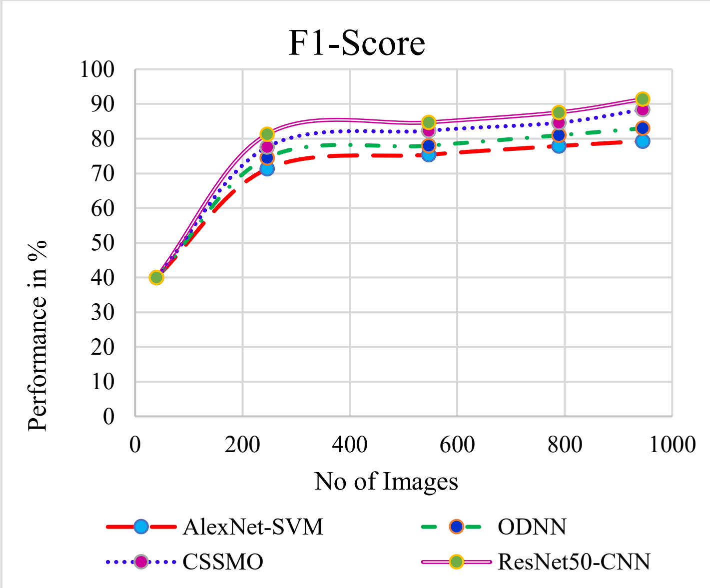


Figure 9. Analysis of F1-Score

In Figure 9, the precision of lung cancer images using the proposed ResNet50-CNN technique is assessed by F1 score analysis. The F1 scores obtained from the analysis show significant improvement in accuracy, with scores of 79.3%, 83.2%, and 88.4% for previous AlexNet-SVM, ODNN, and CSSMO methods and a marked improvement to 91.4% for the proposed ResNet50-CNN method. The F1-score indicates a substantial enhancement in accuracy compared to the earlier methods.

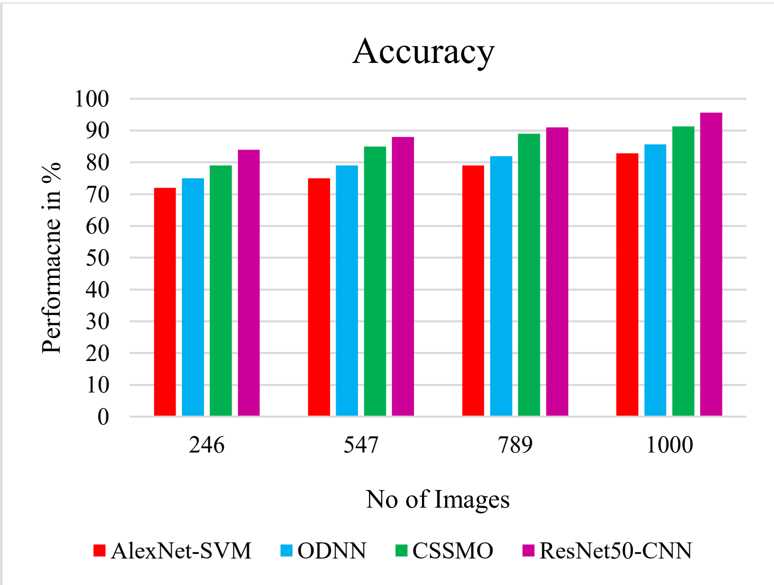


Figure 10. Analysis of Accuracy

The described ResNet50-CNN technique can be used to do a sensitivity analysis on the lung cancer images in figure 7. The accuracy analysis shows a significant improvement in accuracy compared to previous Alex Net-SVM, ODNN, and CSSMO methods, with scores of 82.9%, 85.7%, and 91.3% for the preceding methods, and a considerable improvement to 95.6% for the proposed ResNet50-CNN method. The accuracy performance demonstrates a significant improvement in results compared to earlier methods.

5. CONCLUSION

In conclusion, the dataset of chest CT scan images from Kaggle will increase the precision of lung cancer detection. The GMM models can also be investigated for image preprocessing to improve object-background separation. Furthermore, the EPSO algorithm can evaluate the global optimum location for accurate feature selection in cancer images. Finally, the proposed ResNet50-CNN model uses feature maps based on ResNet50-CNN technique to enhance the accuracy of classifying lung cancer images into cancerous and non-cancerous types. The development of the ResNet50-CNN technique has significantly improved the performance assessment of lung cancer images. The results of the proposed method suggest that clinical imaging can enhance the diagnosis and treatment of lung cancer. Compared to the prior techniques, which yielded accuracy analyses of 82.9%, 85.7%, and 91.3%, respectively, the accuracy analysis of the proposed ResNet50-CNN methodology significantly improved to 95.6%.

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