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Image Processing-Based Lung Cancer Detection Using Adaptive CNN Mixed Sine Cosine Crow Search Algorithm in Medical Applications

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Abstract
Medical image processing relies heavily on the diagnosis of lung cancer images. It aids doctors in determining the correct diagnosis and management. For many patients, lung cancer ranks among the most deadly diseases. Many lives can be saved if cancerous growth is diagnosed early. Computed Tomography (CT) is a critical diagnostic technique for lung cancer. There was also an issue with finding lung cancer due to the time constraints in using the various diagnostic methods. In this study, an Adaptive CNN Mixed Sine Cosine Crow Search (ACNN-SCCS) strategy is proposed to assess the presence of lung cancer in CT images based on the imaging technique. Accordingly, the presented classification scheme is used to assess these traits and determine whether or not the samples include cancerous cells. To obtain the highest level of accuracy for our research the proposed technique is analyzed and compared to many other approaches, and its performance metrics (detection accuracy, precision, f1-score, recall, and root-mean-squared error) are examined.

***Keywords**- Medical Image Processing, Lung Cancer, Computed Tomography (CT), Adaptive CNN Mixed Sine Cosine Crow Search (ACNN-SCCS), Diagnosis.*

I. INTRODUCTION

A popular technology for seeing the inner workings of the body and its illnesses is biomedical imaging. In the field of biomedicine, real-time processing is an essential step in increasing the precision of the detection method. Furthermore, biomedical imaging is used to analyze lethal illnesses like cancer in their early stages, which results in more effective therapies. Cancer is the most deadly illness that claims the lives of people. Using cutting-edge methods, doctors can detect several forms of cancer, such as those found in the lungs, breasts, prostate, and colon. The use of a computerized diagnostic system has been suggested as an innovative method for early finding lung cancer early on. The CAD system raises the bar for efficiency, efficacy, and precision in the detection and treatment of lung cancer. Computer Aided Design (CAD) makes use of digital photographs to highlight the visible areas that are afflicted by the illness (Surendar (2021)). Detecting pulmonary nodules falls within the categorization category. The detection of pulmonary nodules using CT scans of the lungs is crucial for doctors trying to identify the presence of lung cancer. Labeling lung CT scans accurately and their proper categorization is two major issues in the world of practical lung CT image recognition. The use of ensemble learning has overcome the problem of inaccurate classifications. Several machine learning applications have made use of ensemble learning after 30 years of study and are regarded as one of the efficient solutions to the challenge of increasing classification accuracy (Zhang et al. (2021)). To choose features in difficult scenarios, experts often turn to the population-based meta-heuristic known as the Crow Search Algorithm (CSA). The CSA employs the 'crow hunt' strategy, which entails stowing away provisions for eventual retrieval. The research community finds CSA to be a highly appealing tool for many applications since it just has two configurable parameters and offers user-friendly optimizer architecture. Successful applications of CSA include computer science optimization and engineering. However, the CSA is troubled by the slow rate of convergence brought on by the trap of local optimum. The second problem is a lack of convergence since the stochastic character of CSA makes it difficult to define the line between intensification/exploitation and diversification/exploration (Anter and Ali (2020)) there have been many suggested

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algorithms that replicate or mimick natural processes. Numerous suggestions for algorithms that simulate natural processes have been made. The "Crow Search Algorithm" is a meta-heuristic method that imitates the crafty tactics used by crows to steal and hide food. One of the smartest creatures in the world is regarded to be the crow. It is possible to modify these evolutionary algorithms to utilize them for feature selection. The existing work proposes a novel CAD approach to discriminate between abnormal and normal breast masses from mammography images, based on modified wrapper-based chaotic CSA (Reenadevi et al. (2021)). The majority of writers in earlier study publications thought of employing CT scan and x-ray pictures coupled with machine learning (ML) techniques like "Random Forest" (RF), "Support Vector Machine" (SVM)," Bayesian Networks" (BN), and "Convolution Neural Network" to identify and recognize lung cancer (CNN). Histopathological pictures have also been used in certain articles; however, they are less accurate at differentiating between images of carcinomas and non-cancerous tissue. CNN architecture has been taken into consideration in this study report to identify tumors, adenocarcinomas, and squamous cell carcinoma ((Hatuwal and Thapa (2020)).

Figure 1: Lung cancer detection based on image processing

In Figure 1, we see how image processing may be used to detect lung cancer. Lung cancer's disadvantages might lead to issues including shortness of breath. If the lung cancer has spread to the patient's main airways, they may have problems breathing. Fluid accumulation around the lungs, as a result of lung cancer, might limit the capacity of the afflicted lung to completely inflate with each breath.

The major contributions of this paper include:

• To detect lung cancer in its earliest stages.
• To get more precise results via the use of different image processing methods.
• To extract the best features using effective feature extraction and feature selection methods, improving classification accuracy.
• To reduce execution time and error during the categorization process.

Section 2 of the article describes recent related works, Section 3 presents the proposed strategy for lung cancer detection, Section 4 provides details on the findings and discussion, and Section 5 discusses the conclusion and next steps.

II. RELEATED WORKS

The goal of the work by (SR et al. 2019) is to automatically recommend a classification strategy for lung cancer in its early stages. The study uses a Probabilistic Neural Network (PNN) for classification and Computed Tomography (CT) images of the lungs for evaluation. They recommend pre-processing the input lung pictures using the "chaotic crow search algorithm" (CCSA), and then using the "Gray-Level Co-Occurrence Matrix" (GLCM) to extract features. ((Alagarsamy et al. (2021)) studied lung cancer is foreseen using an optimization method based on meta-heuristics. One of the worst illnesses that affect people and do a lot of harm is lung cancer. Nevertheless, a variety of methods for predicting lung cancer have been suggested. But even so, because of the complex structures in the CT scan, predicting cancer has become a difficult challenge. (Luo et al. (2021)) to recommend the best CAD system for detecting lung tumors. After the lung region was segmented and preprocessed, its features, such as the sequence of Zernike moments, were extracted. An enhanced version of the "Support Vector Machine" (SVM) was utilized to make the final diagnostic after features were retrieved. To optimize the SVM, the Enhanced Crowd Search Algorithm (ECSA) is employed as the foundation for this method. Applying the wavelet transform to discrete data and optimizing using a binary crow search (BCSO), they provide a reliable medical picture fusion solution (Parvathy et al., 2020). Here, a pair of picture patterns serve as the system's input, while the merged image serves as the system's output. In this method, the noise contained in the input picture is first removed

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using a median filter, which is then used to improve the image. Then, for both input modalities, a discrete wavelet transform is used. (Kumar et al. (2020)) stated that it is inevitable that met heuristic optimization approaches will be used to address real-world issues. It has been shown that the CSA closely resembles the intelligence of crows. Once considered from an optimization standpoint, crows may be compared to searchers, while their surrounding environment stands in for the problem domain. (Raj et al., 2020) introduced a DL model that takes into account preprocessing, feature selection, and classification to achieve. Medical image classification is based on optimal feature selection. The major objective of this research is to develop a feature selection model for medical picture classification that is very efficient. The Opposition-based Crowd Search (OCS) method is suggested in this research as a way to enhance the performance of DL classifiers. (Raj guru et al. (2021)) makes use of the Pima Indians Diabetes dataset in this way. In this study, the preprocessed PID dataset's non-linear data input is converted into statistically significant linear data using the crow search strategy. The data is then classified using the Random-Forest and K-Nearest Neighbors algorithms. To improve diabetes classification results, this work uses the crow-search optimization technique as a transformation-based approach. (Gupta et (2019)) suggested an upgraded deep feature-based crow-search optimized extreme learning machine to improve the state-of-the-art workings for tackling the healthcare issue. The input mammograms are identified by the publication as either normal or abnormal, depending on previous research. It then concentrates on further categorizing the types of aberrant severity, such as benign type or malignant type. (Prasad et al. (2021) provided a segmentation strategy for lung cancer. The identification of lung cancer and the segmentation of tumors are now regarded as two of the most critical phases of surgical planning and drug preparation. The researchers find it exceedingly challenging to identify the tumor location from the CT (computed tomography) pictures. (Upadhyay et al. (2019)) looks at how image processing and SVM classification may be used to diagnose lung cancer. The study's findings could facilitate cancer diagnosis. The author used segmentation to better examine a lung computer tomography (CT) image. To enhance the quality of an input picture, it is suggested that the water be segmented.

III. PROPOSED METHODOLOGY

Numerous studies in asymptomatic at risk groups have looked at the effectiveness of lung cancer screening utilizing chest X-Rays (CXR) or, more recently, Computed Tomography (CT) with or without other adjuncts such as sputum cytology. Although early disease stage shift is a significant result, death reduction is the gold standard indicator of screening effectiveness. This will lessen the effect of lead time bias, in which earlier cancer identification might seem to enhance survival without really altering the course of the illness. Figure 2 shows the proposed methodology.

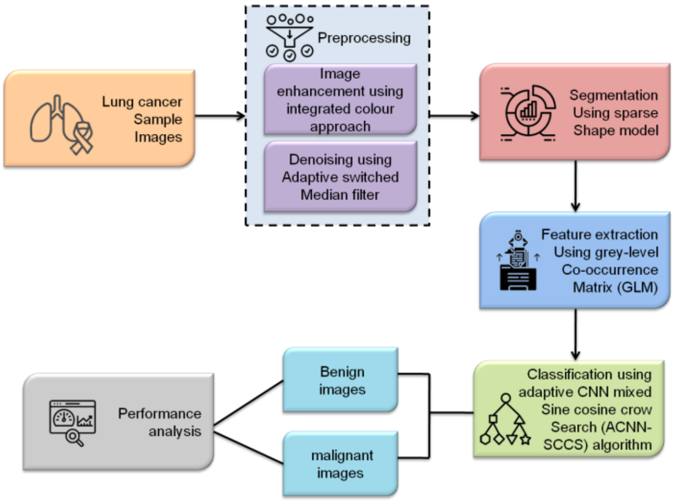

Figure 2: Schematic Diagram of proposed Lung Cancer Detection

A. Data set

To undertake the evaluation of our technique, the Guangdong Lung Cancer Institute prospectively monitored 50 patients who received preoperative CT imaging and surgical dissection from the beginning of 2017. Pathology indicated that half of the nodules in these images were malignant, whereas the other half was linked to benign conditions. The hospital that took part gave its approval after an ethics assessment and collected informed patient consent (Zhang et al. (2019)).

B. Pre-processing

a. Image enhancement using the integrated color approach

The most often utilized attribute in image retrieval and indexing is color. However, because of the inherent error in color quantization and human perception, as well as in the description of the same semantic content, it is crucial to

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include this imperfection when defining characteristics. To better reflect this ambiguity in color indexing, we use integrated color approach.

b. Denoising using Adaptive Switched Median Filter (ASMF)

The SWM filter's main structure is shared by the suggested methodology. A threshold is generated locally from picture pixels instead of being selected a priori, which distinguishes the new approach from SWM. We referred to it as the ASWM filter for this reason. More particular, in the present frame, estimates of the weighted mean value and the weighted standard deviation are generated. The weights are determined by how far a pixel's assessment is from the weighted mean value of the pixels in a certain window.

Therefore, sudden noise does not affect the accuracy of these measurements, which are used to calculate the Threshold. The weighted mean is first iteratively computed for each window. The Threshold is then obtained after calculating the weighted standard deviation. The following is an explanation of this process.

Calculate the weighted mean value N_e in a$(2L+1)\times(2L+1)$ Window W including the current pixel as the first step Variables

$$N_e(x,y)=\frac{\sum_{g,h}\omega_{g,h}I_{x+g,y+1}}{\sum_{g,h}\omega_{g,h}} \quad (1)$$

Where are the weights and the image's grey level at pixel locations i(x,y) and W. At Initialization, these weights are all equal to 1. g and h's index variations are in [-H,H].

step1: $e_{k,h}$ as weight is first estimated.

$$\omega_{g,h}=\frac{1}{|I_{x+g,y+1}-N_e(x,y)|+\delta} \quad (2)$$

Step 2: if$|n_e(x,y)^p|$ <€ where €is a given small value, then stop, else go to step 1 ($n_e(x,y)$ is the weighted mean value at iteration number p)

A tiny number specified as σ prevent division by zero. Then, using a new weighted mean value $n_{e(i,j)}$ is obtained

$$\sigma_e(x,y)=\sqrt{\frac{\sum_{g,h}\omega_{g,h}\left(I_{x+g,y+1}-N_e(x,y)\right)^2}{\sum_{g,h}\omega_{g,h}}} \quad (3)$$

Finally, ASWM can be summarized as follows:

a) Calculate a weighted average and standard deviation based on the weights. $\sigma_{e(x,y)}$in the (2h+1)*(2h+1) window surrounding the current pixel as described above b) Use the following rule:

$$\sigma_e(x,y)=\sqrt{\frac{\sum_{g,h}\omega_{g,h}\left(I_{x+g,y+1}-N_e(x,y)\right)^2}{\sum_{g,h}\omega_{g,h}}} \quad (4)$$

As previously mentioned, calculate the weighted mean$n_e(x,y)$ and the weighted standard deviation $\sigma_{e(x,y)}$ in the window (2h+1)*(2h+1) surrounding the current pixel.

Where $n_{x,y}$ the median in the window is $e_{x,y}$, is a given parameter and represents the local threshold$\alpha*\sigma_e(x,y)$.

$$\hat{J}_{x,y}=\begin{cases} n_{x,y}, & if\,|I_{x,y}-N_e(x,y)|>\propto\times\sigma_e(x,y), \\ I_{x,y}, & otherwise \end{cases} \quad (5)$$

To do this, change the αvalue. Based on simulations performed on a wide range of pictures, the following approach producesα good outcomes, that is

$$(5)\propto_0=20, and\ \propto_{n+1}=\propto_n*0.8(m\geq 0) \quad (6)$$

Where α_o are the first step's parameter and the α_nTh step's parameteα_nr. While σ_e is low in smooth areas, it rises too high levels along edges and in areas with roughness. This flexibility is crucial for retaining picture quality. The proportion of noise also does not affect this trend.

C. Segmentation using Sparse Shape Model

As a regularization step during deformation, sparse shape before modeling may be used to shape refinement methods. The picture gradient information is used to distort a starting shape. Shape refinement is used as high-level constraints throughout the deformation process to prevent becoming trapped in local minima of the picture information. n.

$$\arg\min_{i,w,\beta} \|P(j,\beta)-Si-w\|_2^2+\lambda_1\|I\|_1+\lambda_2\|w\|_1,$$
(7)

We will refer to the intermediate deformation result as y_s, and the training shape matrix Ds. Then, using $D_s$and y_s, x may be calculated. $D_s{}^x$is was reshaped to serve as the refined form.

Since the model is generally aligned after initialization, it is possible that e will not take on huge values throughout this

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refining operation. Small mistakes that don't follow a Gaussian distribution still need to be modeled, however.

D. Feature extraction using grey level co-occurrence matrix

A co-occurrence matrix is a method for obtaining textural details about the grey level transition between two pixels. Such a matrix depicts the joint distribution of contiguous gray-level pair distributions given a spatial connection determined among texture's pixel's established spatial relationships As a consequence, matrices that convey different types of information may be constructed simply by altering the spatial relationship. These matrices are used to extract descriptors. The co-occurrence matrix's rows and columns are solely determined by the texture's grey levels and not by the size of the picture. To make the co-occurrence matrix smaller, quantizing the range of grayscale intensities is standard practice. The normal number of bins is between 8 and 256. The two information measures of correlation, the maximal correlation coefficient, the angular second moment, the sum of squares, the inverse difference moment, the sum average, the sum variance, the sum entropy, the sum entropy, the difference variance, and the differential entropy are just a few of the fourteen statistical measures.

E. Classification using adaptive CNN mixed sine cosine crow search algorithm

With adaptive CNN, accurate identification is possible while using less memory. This is done by decreasing the number of kernels and layers required in the conventional CNN setup, as well as memory use, and by boosting the training speed and the number of activation functions by 2X. Crows are thought to be intelligent birds by scientists. Their brain size is substantial compared to their physical size. The crow has a reasonable tendency to steal food from other birds. They continue to watch other birds learn where they conceal their food. Crows might then steal other birds' food when they emerged from their hiding location if they did this.

$$I_x^{p+1} = \begin{cases} I_x^p + q_x \times ch_x^p \times \left| n_x^p - I_i^p \right| & q_x \geq ZT_x^p \\ a\ random\ position\ otherwise \end{cases}$$

(8) Crows use a variety of methods to achieve this. Researchers were inspired by crows' behavior to create the initial iteration of the crow search algorithm. According to the "Crow Search Algorithm" (CSA), crows relocate depending on the following calculation while taking other birds' awareness into account Consider the crow's perceptual awareness. When the afflicted bird realizes that a crow is pursuing it, it will attempt to lead the crow somewhere completely at random. Please take note that the location of crow I am updated by picking a crow j at random. In this case, j represents consciousness and AP indicates the crow. The victim bird would attempt to lead the crow to a random spot if he learned that the crow is following him. It should be noted that a crow j is chosen at random to update the location of each crow i.

Algorithm 1: Crow search algorithm

```
for x=1: number of initial solutions
        for y=1:m
        pop (x,y) =create a random solution
Fitt (x)=obj (pop(x,:);
    end for
end for
Chose best-sol
while (index < maximum number of generation)
Update r1, r2, r3, r4
for each search individual
p=random number in (0,1]
if (p<0.5)
        I_x^(p+1)=I_x^p+q_1×sin(q_2 )×|q_3 T_x^p-I_x^p|
    else if (p>0.5)
        I_x^(p+1)=I_x^p+q_1×cos(q_2 )×|q_3 T_x^p-I_x^p|
    end if
end for
  Calculate fitness
  Update best-sol
```

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index = index +1

end while

The location of the particles is updated using the sine cosine algorithm (SCA) which was only recently presented. Using the formula below, the SCA adjusts the position of the particles in solution space to the optimal solution. Where r1; r2; r3 are integers produced at random in the range of (0, 1), $where X_i^t$ *is* the current location, and Pt is where the finest solution is located.R1 indicates the update direction, R2 establishes the updating distance, R3 establishes random weights to maintain a correct trade-off between the emphases and de-emphasis in the desalination and R4 selects a sine or cosine movement.

$$I_x^{p+1} = \begin{cases} I_x^p + q_1 \times \sin(q_2) \times \left| q_3 T_x^p - I_x^p \right|, & q_4 < 0.5 \\ I_x^p + q_1 \times \cos(q_2) \times \left| q_3 T_x^p - I_x^p \right|, & q_4 \geq 0.5 \end{cases} \quad (9)$$

IV. RESULT AND DISCUSSION

The proposed method outperforms the majority of algorithms in solving the issue, and the information about algorithms is revealed. This finding indicates that the proposed method is a reliable method with the minimum deviation from the ideal result across all repeats.

A. Accuracy

Higher accurate cancer nodule diagnosis than the best available model decides whether the lung cancer found is benign or malignant. An adaptive CNN mixed sine cosine crow search method is described with 91% accuracy. In this instance, the advised strategy's accuracy has increased. Figure 3 displays the accuracy analysis.

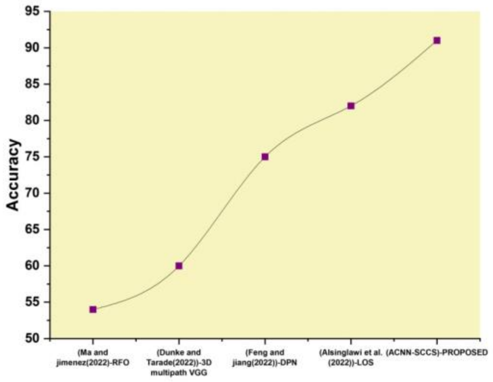

Figure 3: Analysis of accuracy for lung cancer detection

B.Precision

Precision has had a significant influence on diagnostic pathology in the treatment of lung cancer, and it also offers a better understanding of the molecular basis of the illness. A mixed sine-cosine crow search adaptive CNN described a 93% level of precision. The precision of the suggested approach has improved in this case. Figure 4 displays the precision analysis.

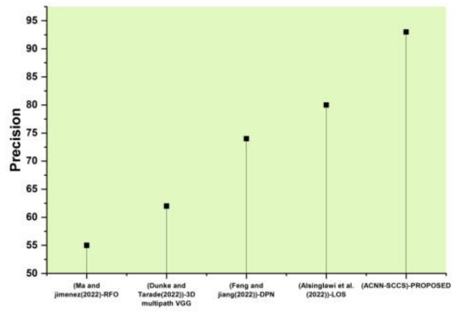

Figure 4: Analysis of precision of lung cancer detection

C. F1 score

The F1 score is the mathematical mean of the two sub-scores, recall and accuracy. It's a measure of performance based on statistical analysis. In other words, an F1 score is a mean of a method's performance based on two elements, namely accuracy, and recall (from 0 to 9, with 0 being the lowest and 9 the most). An adaptive CNN mixed sine cosine crow search method is described with a 98% F1 score. In this instance, the advised strategy's accuracy has increased. The analysis of f1 score shown in Figure 5.

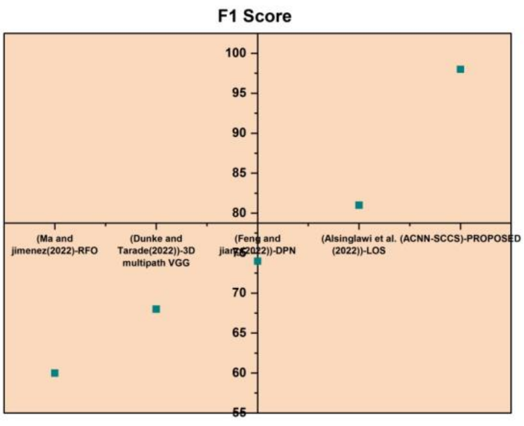

Figure 5: Analysis of F1 score for lung cancer detection

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D. Recall

Patients with a recent lung cancer diagnosis have a low level of understanding and satisfaction with the communication of treatment goals. Patients who remembered the treatment procedure's details accurately expressed much higher levels of satisfaction with its communication. With a 94% recall, an adaptable CNN mixed sine cosine crow search strategy is shown. The recall of the suggested method has improved in this case. Examining the lung cancer detection recall is shown in Figure 6.

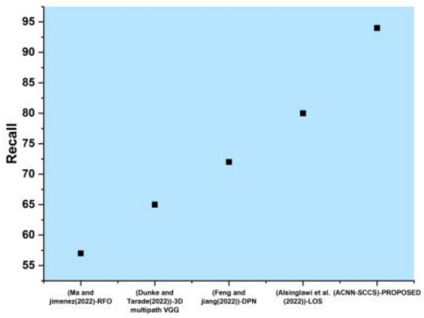

Figure 6: Recall of lung cancer detection

E. Root Mean Square Error (RMSE)

One common metric used to assess the precision of a model is the Root-Mean Squared Error (RMSE). It establishes the model's correctness. Root Mean Square Error (RMSE) is used to measure classification accuracy and discern between the dependability and credibility of the data acquired. An adjustable CNN mixed sine cosine crow search technique is shown with a 95% RMSE. In this instance, the proposed method's RMSE has decreased. The Root Mean Square Error in Lung Cancer Detection is depicted in Figure 7.

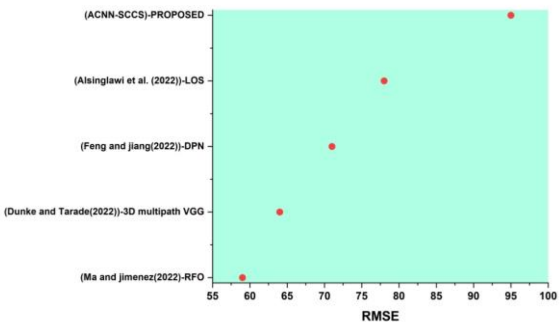

Figure 7: RMSE of lung cancer detection

V. CONCLUSION

The fact why lung cancer is so deadly and so common may be traced back to the fact that it is usually detected at an advanced stage when cancer cells have already spread throughout the lungs. Early identification of lung cancer is crucial in preventing advanced stages of the disease and lowering the global prevalence rate. In this study, CT scans from the Kaggle data set are analyzed. The paper proposed (ACNN-SCCS) to evaluate CT scans for the presence of lung cancer. We broke down the method into three distinct phases—preprocessing, segmentation, and feature extraction— to ensure the highest quality of work. Experimental findings are presented with 91% accuracy, 94% recall, 93% precision, 98% F1 score, and 95% RMSE. The proposed technique is more successful than existing methods. As extra information becomes available for analysis, we will be able to boost the research's efficiency significantly.

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