TPM Vol. 32, No. S4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

LUNG CANCER DETECTION USING IMAGE PROCESSING TECHNIQUES

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Abstract
An all-in-one framework of integrated image processing for precise lung cancer detection in CT images, comprising sophisticated pre-processing, segmentation and classification and extensive performance evaluation, is proposed in this work. Pre-processing with Anisotropic diffusion filtering at first is performed, which improves or enhances the quality of the image quality by getting rid of noise while maintaining the necessary edges and fine physiological structures of the image. Then, segmentation in Morpho-Geometric Region Segmentation (MGRS) is applied to correctly extract candidate tumour regions, which can further separate the nodules from the surrounding tissues by characteristics such as shape, size, and compactness. For classification, we use a fusion of Stacked Neural Network (SNN) and Optimized Deep Neural Network (ODNN) to achieve better diagnostic accuracy by studying complex features and model parameters in better tuning. The proposed method is compared with the other two methods by accuracy 96.84%, Recall 97.10%, specificity 96.45 %, precision 96.92% and F1-score 96.99% to confirm the performance of reliable identification between malignant and benign nodules. Experimental results indicate that the proposed integrated method is effective in achieving higher classification accuracy and strong generalizability, for early diagnosis of lung cancer and improving clinical decisions in lung cancer detection.

Key Words: Anisotropic diffusion filtering, Morpho-Geometric Region Segmentation, Stacked Neural Network, Optimized Deep Neural Network

INTRODUCTION

Millions of new instances of lung cancer are identified each year, making it the leading cause of cancer-related death globally. To identify lung cancer, pathologists physically examine histology slides; this is a time-consuming, inaccurate, and human error-prone process [1]. Tumor formation results from the disease's unchecked expansion of lung cells, which interferes with regular cellular division processes. They are both benign (non-cancerous) and malignant (cancerous) tumours can develop [2].

Research indicates that a healthy person can be affected by 19 different types of cancer. Among these cancers, lung cancer has the highest fatality rate. Each year, over 1.7 million individuals are expected to die from this illness [3]. Early cancer identification presents extremely difficult obstacles. In its early stages, it frequently exhibits relatively mild symptoms or stays asymptomatic, making it challenging to identify. Timely diagnosis is a difficult endeavour since the tumour typically progresses by the time symptoms appear [4]. This is particularly advantageous for data professionals responsible for collecting, processing, and understanding vast amounts of data, as it speeds up and streamlines the process [5].

Objectives

- To accurately isolate potential tumour regions using Morpho-Geometric Region Segmentation by integrating morphological operations and geometrical feature analysis.
- To improve diagnostic precision by employing a hybrid classification approach that fuses Stacked Neural Networks and ODNN for effective learning of complex features and fine-tuning model parameters.

The remaining portion of the document is divided into significant sections, which are described as follows: Section II examines the current research efforts in Lung Cancer Detection Using Image Processing Techniques used by different authors. The workflow of the suggested approach is explained in Section III and consists of pre-processing, segmentation and classification models. Section IV presents the findings analysis and performance data. Section V presents the conclusion.

RELATED WORK

Lung cancer is still one of the largest causes of cancer-related deaths worldwide. Early and accurate diagnosis is required to increase survival rates [6]. These limitations have sparked a growing interest in automated systems powered by intense learning to augment radiological assessments. Computer-aided diagnostic systems now operate much better because of recent developments. Artificial intelligence use in data processing and decision-making is growing in importance. However, researchers are still working to find the best methods for clinical use [7]. AI offers many benefits in medical imaging, however, there are still challenges, such as protecting patient data, making AI decisions more straightforward to understand, and ensuring AI models work well in different hospitals and clinics.

Reducing the number of lung cancer patients requires early diagnosis of lung nodules. Because of its high resolution, Computed Tomography remains the standard imaging method for lung cancer screening. CNN-based approaches face challenges such as limited annotated datasets, intra-class variation, inter-class similarity, and manual labelling difficulties, which affect model training and reliability [8]. In Malaysia, lung cancer continues to rank among the top causes of mortality, especially among men. Reducing death rates requires early and precise detection. Models such as Exception, and Mobile Net have shown promising results. Initially trained on large-scale image datasets, these networks are fine-tuned for medical image analysis with modifications including added layers number of epochs, and optimizer configurations [9].

It is critical in increasing nodule detection sensitivity while minimizing false positives common limitations in traditional computer-aided diagnostic systems. [10].Colon and lung cancer image classification remains critical for early diagnosis and improved patient outcomes. Recent work has introduced two novel dense architectures, D1, D2, specifically designed to enhance histopathological and CT scan image classification accuracy [11].

A new transfer learning-based framework called VER-Net was recently introduced. It uses CT scan pictures to detect lung cancer by stacking three distinct transfer learning models. According to experimental evaluations, VER-Net continuously outperformed eight other cutting-edge transfer learning models. Beyond lung cancer, the VER-Net architecture also shows potential applicability in detecting other diseases using CT imaging, further broadening its clinical utility [12]. Lung cancer continues to be a primary cause of cancer-related deaths globally systems that use medical imaging modalities have emerged as crucial tools for improving diagnosis accuracy. [13].

A novel framework known as EXACT-Net has been proposed to address this issue. This model integrates information extracted from electronic health records using a pre-trained large language model with a zero-shot learning approach to reduce false positives while preserving accurate positive detections effectively. This represents a significant breakthrough in automated tumour segmentation and could speed up precise treatment planning in clinical practice [14].Lung cancer is frequently discovered at an advanced stage, and the efficacy of current therapies is severely constrained. Generative Adversarial Networks are optimized using the Slap Shuffled Shepherd Optimization Algorithm for precise segmentation, and the VGG16 convolutional neural network for classification [15].

Numerous research has looked into how machine learning algorithms might help detect lung cancer early and help doctors decide whether more conservative monitoring or comprehensive diagnostics are needed. These ensemble methods, particularly Boost, offer a promising direction for developing reliable and cost-efficient lung cancer screening tools [16]. Recent studies have investigated approaches to improve predictive capacities utilizing common diagnostic data to address this difficulty. These findings underscore the promise of DL-based systems in stratifying NSCLC patients by metastatic risk using routine histopathological slides [17].

A computer-aided diagnosis system utilizing three state-of-the-art deep learning architectures—ResNet-50 leveraging transfer learning to classify lung cancer images from the LIDC-IDRI dataset, comprising 1,000 DICOM images categorized into four classes. The researchers implemented data augmentation strategies to mitigate overfitting and enhance generalizability [18]. The most common are convolutional neural networks, which are good at recognizing image patterns. 2D and 3D CNNs are used 3D CNNs are especially useful for analyzing CT scans because they consider multiple image slices together. Many studies use public datasets such as LUNA16, and JSRT. Since their performance occasionally declines when evaluated on data from several sources [19].

This study uses advanced image processing techniques to improve how breast cancer is diagnosed using histopathology images (microscopic tissue samples). Among all the models, LGBM performed the best. The method was also successfully tested on another dataset for lung colon cancer [20].

PROPOSED METHODOLOGY

The proposed methodology for lung cancer detection involves a multi-step process. Morpho-Geometric Region Segmentation is used to accurately extract candidate tumour regions based on geometric features like shape, size, and compactness. For classification, a hybrid model combining Stacked Neural Networks and Optimized Deep Neural Networks is employed to achieve higher diagnostic accuracy.

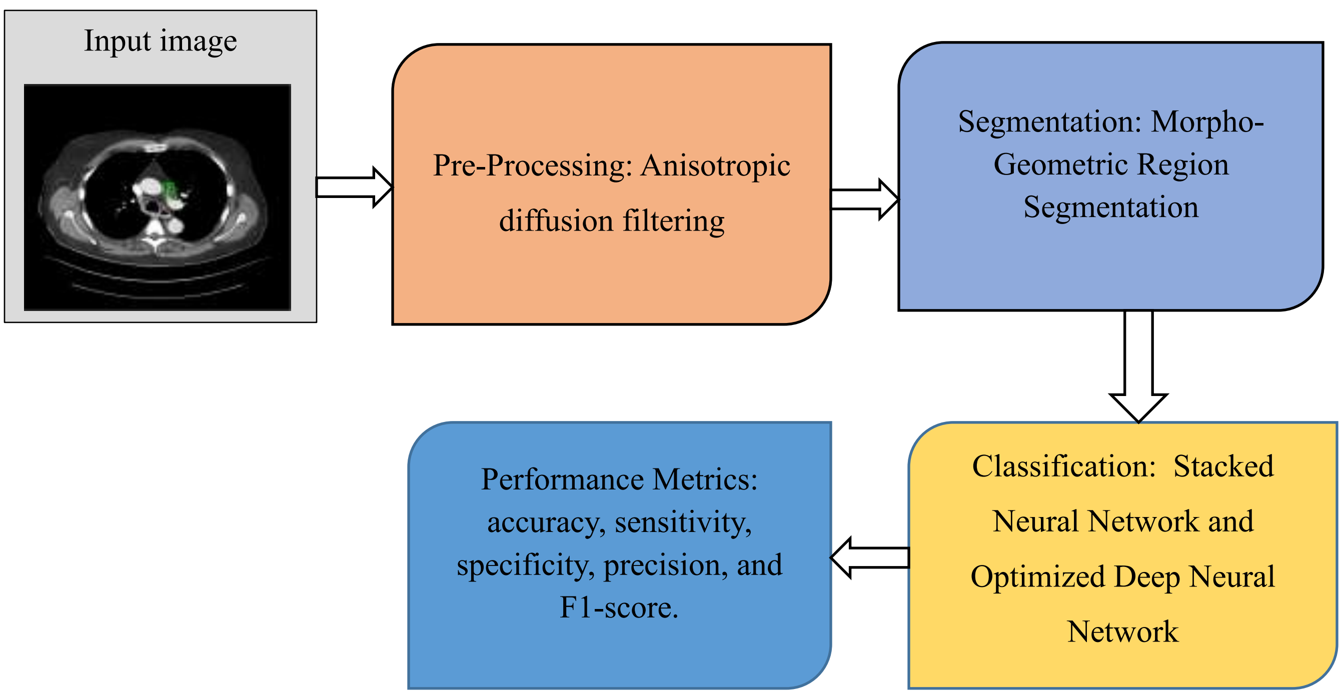

Figure 1 Proposed Methodology Architecture

3.1) Pre-Processing: Anisotropic diffusion filtering

Anisotropic diffusion filtering is a technique to reduce noise in lung CT images while maintaining important edges such as the boundaries of lung nodules. It smoothens homogeneous regions without blurring sharp structures and thus provides a clear visualization of tumours. This brings the contrast between cancerous nodules and adjacent tissues to a higher degree and consequently results in improved accuracy of the subsequent segmentation and feature extraction steps of lung cancer detection.

$$\frac{\partial f(i,l,r,t)}{\partial t} = div[q(i,l,r,t)], \tag{1}$$

Where $(i, l, r,)$ is are image intensity at the spatial location and diffusion time t, $\frac{\partial f}{\partial t}$ is are rate of change image intensity at location overtime t, $and\ div[q]$ is a divergence of diffusion flux. This coefficient controls how much smoothing is applied to different regions of a lung CT image, For example, $q(i, l, r, t)$ is expressed as follows:

$$q(i,l,r,t) = \frac{1}{1+\left[\frac{|\nabla f(i,l,r,t)|^2}{f(i,l,r,t)^2} - p^2\right]/(p^2(1+p^2))} \tag{2}$$

The Equation for the Diffusion coefficient represent is,

$$q(h) = \frac{1}{1+[h^2(i,l,r,t)-h_0^2]/[h_0^2(t)(1+h_0^2(t))]} \tag{3}$$

$$h_o(t) = \frac{\sqrt{var[z(t)]}}{z(t)} \tag{4}$$

In lung cancer detection using images, Where $var[z(t)]$ represents the intensity variance, and $z(t)$ is the average intensity value of the lung tissue surrounding a voxel at position t.

For High Contrast edges:

$$g[\nabla I] = e^{-\left(\frac{||\nabla||}{k}\right)^2} \tag{5}$$

This equation (5) keeps sharp edges preserved by applying less smoothing where the gradient is high. The Gaussian exponential function keeps the sharp tumour edges on lung CT images intact to make accurate detection.

For wider regions:

$$g[\nabla I] = \frac{1}{1+\left(\frac{||\nabla||}{k}\right)^2} \tag{6}$$

The equation (6) applies more smoothing to regions where the gradient is low reducing noise and keeping the image clean while still preserving lung cancer boundaries.

3.2) Segmentation: Morpho-Geometric Region Segmentation (MGRS)

Morpho-geometric region Segmentation of lung cancer detection separates possible tumour regions from other regions by integrating morphological operations and geometrical analysis. Morphological processing- It improves and isolates the segmentation of lung nodules from CT images for the first time. Shape and size also play important roles; attributes such as the axe's length and the area ratio of the nodules are used to distinguish bad nodules and non-nodule tissues. Spot area and compactness serve as aggregate metrics to characterize the tumour-like regions.

$$g = C_T - (C_T \ominus E_s) \tag{7}$$

Where C_T is the original CT image of the lung, E_s is are structuring element used for morphological erosion, and g is the boundary-enhanced region obtained by subtracting the eroded image $(C_T \ominus E_s)$ from the original CT image C_T.

$$e_{cc}(i,j) = 2 * \left\{\left(\frac{B_y M_{axis}}{2}\right)^2 - \left(\frac{B_y R_{axis}}{2}\right)^2\right\}^{\frac{1}{2}} \tag{8}$$

$$M_{axis} = g_i + f_j \tag{9}$$

$$R_{axis} = \left\{\left(g_i + f_j\right)^2 - dis\right\}^{\frac{1}{2}} \tag{10}$$

Where $e_{cc}(i,j)$ is the elliptic contour component, M_{axis} the semi-major axis length, $g_i + f_j$ Describing the longer dimension of the region, the R_{axis} the semi-minor axis length, derived by adjusting M_{axis} with a distance factor dis, representing the shorter dimension of the region.

$$Spot_A = \sum_{i,j}^{T} e_{cc}(i,j) \tag{11}$$

Where $Spot_A$ is the cumulative spot area, calculated by summing all elliptic contour components (i,j).

$$A_{ratio} = \sum_{i,j}^{T} \frac{Spot_A W_h}{Spot_A H_t} \tag{12}$$

Where A_{ratio} is the aspect ratio, w_h is the width of the segmented spot area, H_t is the height of the segmented spot area.

$$y_t = \sum_{i,j}^{T} \frac{A_{ratio}}{MiniB_{area}} \tag{13}$$

Where $MiniB_{area}$ is are area of the minimal bounding box that encloses the segmented region, y_t is the regional yield.

3.3) Classification: Stacked Neural Network and Optimized Deep Neural Network

The stacked network combines two-dimensional features, including shape, texture, and CT density computed from segmented CT images, to model complex patterns of malignant and benign nodules. Each layer gradually learns features, making the model more sensitive to subtle differences between cancerous and non-cancerous patches. The SNN overcomes overfitting and ensures robustness by combining the outputs of multiple networks.

$$y_t = f(y_{t-1,}y_{t-1,} \dots y_{t-s}) \quad (14)$$

Where y_t is are predicted output at time step t, which depends on previous outputs $(y_{t-1,}y_{t-1,} \dots y_{t-s})$. It represents the model's forecast based on historical data.

$$\tanh(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \quad (15)$$

Where $\tanh(x)$ is are hyperbolic tangent activation function, which transforms input values into a range between -1 and +1, helping to introduce non-linearity in the model.

$$exp(x) = e^x \quad (16)$$

$$y_t^n = \tan h\left(\sum_i w_i^n . \left(\tanh\left(\sum_p w_{p.q}^n . y_p - \theta_q^n\right)\right) - \theta^n\right. \quad (17)$$

Where exp(x) is the exponential function , y_t^n is the output of the n-th neuron at time t, w_i^n the weight connecting input t. $w_{p.q}^n$ The weight connecting the *p*-th previous layer neuron to the *q*-th neuron in the current layer for neuron *n,* y_p is The output of the *p*-th neuron in a previous layer, θ_q^n The bias term associated with the *q*-th neuron for neuron *n.*

In lung cancer recognition, the process of fine-tuning network parameters for getting an accurate and precise diagnosis improves classification performance. ODNN uses a deep hierarchical architecture to automatically learn complex features of lung CT images, including texture, shape, and intensity fluctuation that can be associated with nodules.

$$y_t^n = T_{v,1}^l(a_1, g) + \mathcal{T}_{v,2}^{\mathcal{L}}(a_2, g) + \cdots + \mathcal{T}_{v,k}^{L}(A_k, g) + T_{v,0}(l) \quad (18)$$

Where y_t^n represents the output of neuron n at time t, $\mathcal{T}_{v,k}^{L}(A_k, g)$ applied to various features.

$$N^h = \sum_{v=0}^{z_m} T_{h,v}^m \, b_{v,g}^{m} \quad (19)$$

Where N^h represents the aggregated activation for neuron h in layer m, obtained by summing the weighted transformations $T_{h,v}^m$ applied to the feature-adjusted biases$b_{v,g}^{m}$.

$$h = \begin{cases} e_h = s_m(N_h) \\ s_{m_{N^h}} = \frac{c_{N_h}}{\sum_{s=0}^{1} c^{N_s}} \end{cases} \quad (20)$$

The variable h indicates the neuron's output state, which can be computed either through a softmax function $s_m(N_h)$ as a normalized probability score $s_{m_{N^h}} = \frac{c_{N_h}}{\sum_{s=0}^{1} c^{N_s}}$, ensuring the output represents class probabilities.

RESULT & DISCUSSION

The experimental result of the proposed integrated framework, including Anisotropic Diffusion Filtering for pre-processing, Morpho-Geometric Region Segmentation for segmentation and a hybrid Stacked Neural Network–Optimized Deep Neural Network for classification was evaluated rigorously using a baseline lung CT image dataset.

4.1) Evaluation Metrics

Table 1 Evaluation Metrics Formulas

S.No	Metrics	Formula
1	Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
2	Precision	$Precision = \frac{TP}{TP+FP}$
3	Recall	$Recall = \frac{TP}{TP+FN}$
4	Specificity	$\text{Specificity} = \frac{TN}{TN+FP}$
5	FI-Score	$FI - Score = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+ Recall}}$

TPM Vol. 32, No. S4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

4.2) Dataset Description

The Iraq-Oncology Teaching Hospital/National Centre for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset was collected over three months in the fall of 2019 at the speciality hospitals stated above. Included are CT scans of patients with different stages of lung cancer as well as those of healthy people.

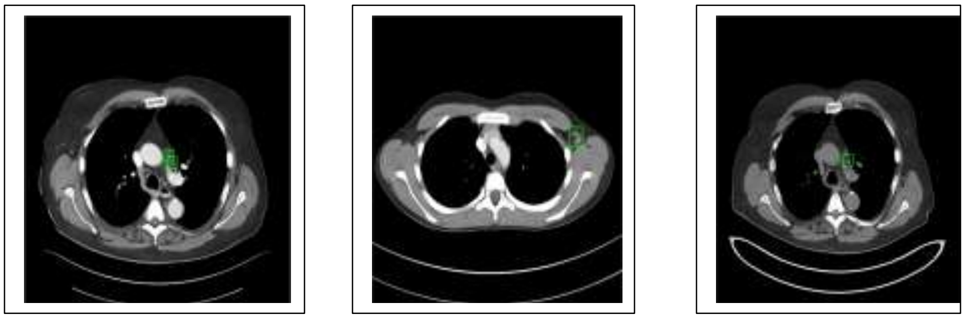

Figure 2 Lung Cancer Images

Figure 2 illustrates various lung cancer images from CT scans, showcasing different stages and types of tumours. The images highlight both malignant and benign nodules, emphasizing their size, shape, and texture differences. The regions of interest are marked for segmentation and classification analysis.

4.3) Comparison Results

Table 2 comparative results

Methods	Accuracy	Recall	Specificity	Precision	FI-Score
Convolutional Neural Network	93.15%	91.45%	94.00%	92.11%	91.77%
VGG16	90.48%	89.72%	91.25%	89.95%	89.83%
Support Vector Machine	92.56%	90.12%	94.05%	91.23%	90.66%
Random Forest	94.12%	92.24%	95.87%	93.45%	92.89%
Proposed SNN+ ODNN	96.84%	97.10%	96.45 %	96.92%	96.99%

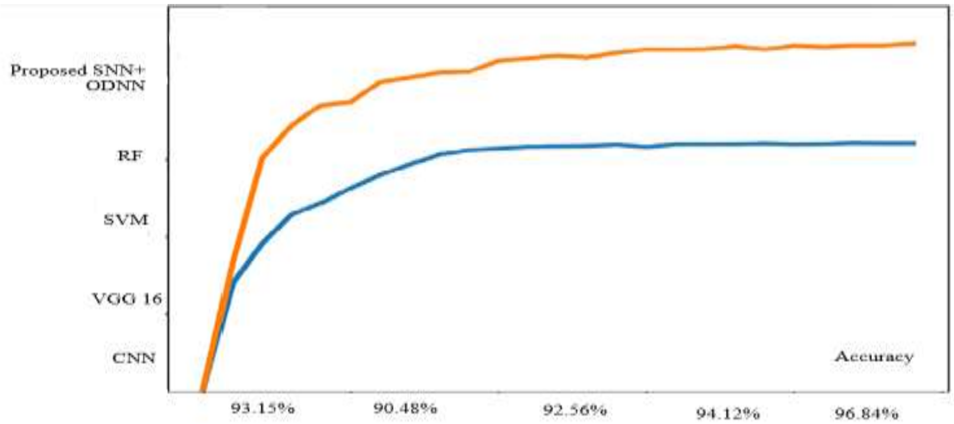

Figure 3 Illustrates Accuracy Performance

Figure 3 shows the comparative accuracy performance of 5 different classification methods used to detect lung cancer in CT images. The proposed hybrid model had the highest accuracy of 96. 84% compared to the other classification methods tested. The next best performance is provided by the Random Forest classifier with 94. 12%. The Convolutional Neural Network has an accuracy rate of 93. 15% compared to the previous three models due to its spatial feature learning ability. Moreover, the SVM has an accuracy rate of 92. 56%, Therefore, VGG16 was found to have the lowest accuracy levels at 90. 48% despite the deep CNN architecture.

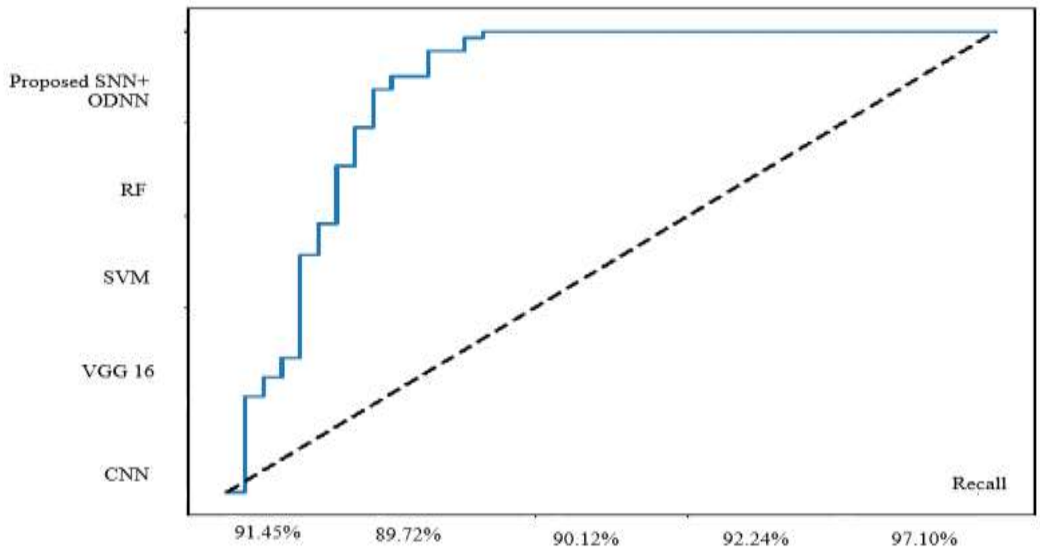

Figure 4 Illustrates Recall Performance

Figure 4 shows the recall performance of five classification methods used for the detection of lung cancer in CT images. The SNN + ODNN model achieved the highest recall of 97. 10%. The Random Forest classifier followed the above-mentioned classification method with the highest recall of 92.24%, The Convolutional Neural Network classified the image as 91. 45% and the Support Vector Machine to 90. 12%, which indicates moderate performance in accurately detecting positive cases and a higher risk of missing the presence of malignant nodules compared with RF and the proposed framework. The lowest recall of VGG16 is 89. 72%.

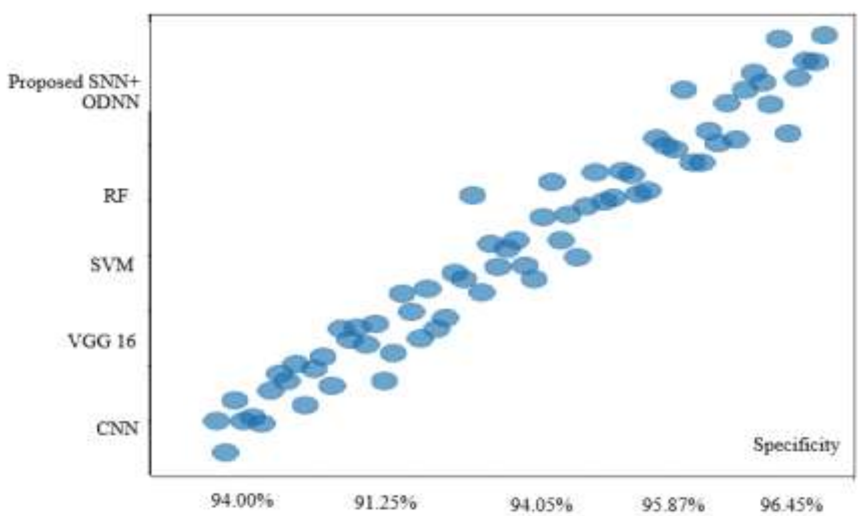

Figure 5 Illustrates Specificity Performance

Figure 5 shows the specificity comparison of five classification methods for lung cancer detection. The proposed SNN + ODNN achieved the highest specificity of 96.45%, demonstrating a superior ability to correctly identify benign cases and reduce false positives. Random Forest followed with 95.87%, while SVM and CNN achieved 94.05% and 94.00%, respectively. VGG16 recorded the lowest specificity of 91.25%. The scatter plot confirms the consistent superiority of the proposed method. This high specificity ensures reliable discrimination between benign and malignant nodules, aiding accurate clinical decisions.

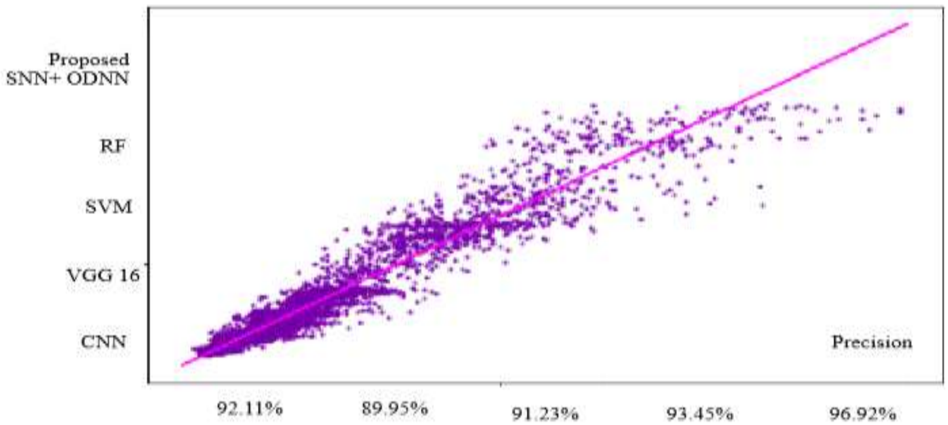

Figure 6 Illustrates Precision Performance
Picture 6: Precision Performance Comparison of Five Classification Methods for Lung. The proposed SNN + ODNN model provides the highest precision of 92%, reflecting its excellent performance in minimizing false positives by accurately identifying malignant nodules. The results for Random Forest are 45%, CNN is 11%, and SVM is 23%, while VGG16 has the lowest precision at 95%. The dense scatter distribution and magenta trend line indicate the higher precision of the proposed method.

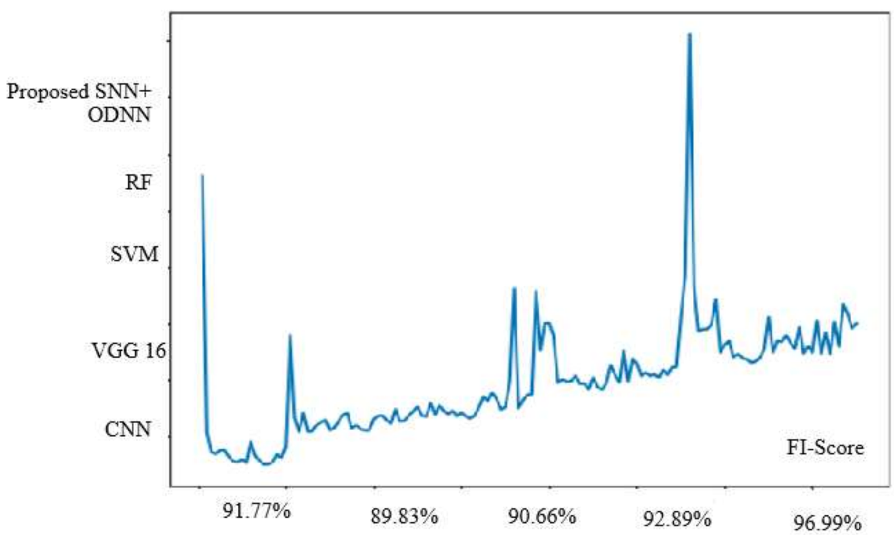

Figure 7 Illustrates FI-Score Performance
Figure 7 illustrates the FI-Score performance for different machine learning models and methods. As observed, the Proposed SNN+ODNN method yields the highest FI-Score, reaching 96.99%, which demonstrates its superior performance in comparison to the other methods. RF, SVM, VGG 16, and CNN all show lower FI-Scores, with values ranging from 89.83% to 92.89%. This suggests that the proposed hybrid approach outperforms these traditional methods, highlighting its potential to achieve higher accuracy in the task at hand.

CONCLUSION

A conclusion proposed an all-in-one framework for lung cancer detection in CT images that effectively utilises state-of-the-art image processing techniques such as anisotropic diffusion filtering, morpho-geometric region segmentation and hybrid classification models of stacked neural network and Optimised Deep neural network to efficiently improve the image quality. The pre-processing step improves image quality by removing noise while conserving critical features. Additionally, the hybrid classification model improves classification accuracy by leveraging complex features and optimisation. Extensive evaluation of the proposed method indicates that it outperforms other approaches concerning accuracy 96.84%, Recall 97.10%, specificity 96.45 %, precision 96.92% and F1-score 96.99% which shows the potential of the method for early and reliable lung cancer diagnosis. The proposed frameworks have shown excellent generalizability and ability to contribute to better clinical decision-making.

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