

RESEARCH ARTICLE

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AN OPTIMIZED HYBRID FUSION MODEL COMBINING DENSE AND VISUAL GEOMETRY NETWORKS WITH MACHINE LEARNING FOR LUNG CANCER DETECTION AND CLASSIFICATION

Umakanth Basineni*¹, Fahimuddin Shaik*²

¹Research Scholar, Annamacharya University, Rajampeta-516126, AndhraPradesh. India

²Associate Professor, Department of ECE, Annamacharya University, Rajampeta-516126, AndhraPradesh. India.

¹<http://orcid.org/0009-0008-0002-2513>, ²<http://orcid.org/0000-0001-6852-7851>

E-mail: *umakanth.info@gmail.com, fahimait@gmail.com

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ABSTRACT

Lung cancer remains one of the leading causes of cancer-related mortality worldwide, underscoring the critical need for accurate and early diagnostic solutions. By integrating Densely Connected Convolutional Network (DenseNet), Visual Geometry Group Network 19 (VGG19), and Multi-Class Support Vector Machine (MCSVM) into a hybrid architecture termed OncoFusion-Net, this study introduces a robust framework for the early and precise detection and classification of lung cancer. To enhance image contrast and suppress noise while preserving essential structural information, high-resolution Computed Tomography (CT) images are preprocessed using Anisotropic Diffusion Filtering (ADF) and Contrast Limited Adaptive Histogram Equalization (CLAHE). Segmentation is accomplished through Kapur's Entropy-Based Thresholding Method, effectively isolating suspicious regions of interest. For feature extraction and representation, OncoFusion-Net harnesses the combined advantages of VGG19 and DenseNet, ensuring efficient feature reuse and propagation. The resulting features are classified using MCSVM, facilitating accurate differentiation among benign, malignant, and other lung cancer types. The model's performance is rigorously validated on independent datasets, demonstrating high accuracy, sensitivity, and reliability, further confirmed through Receiver Operating Characteristic (ROC) curve analysis. Overall, this comprehensive framework advances lung cancer diagnosis by enabling early detection and supporting personalized treatment planning to improve patient outcomes.



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I. INTRODUCTION

A timely and precise diagnosis is essential for successful treatment and higher survival rates for lung cancer, which continues to be one of the world's top causes of cancer-related death [1-3]. Even though they are crucial, traditional diagnostic techniques can have limitations in terms of accuracy and scalability, particularly when handling complicated imaging data [4]. In this regard, the development of sophisticated computer models presents a revolutionary opportunity to improve lung cancer diagnosis and classification using automated, precise, and effective techniques [5-9]. Utilizing high-resolution computed tomography (CT) images, the system guarantees access to detailed structural information required for identifying abnormalities such as nodules or tumors [10-13]. The suggested methodology makes use of OncoFusion-Net, a novel hybrid model designed to integrate state-of-the-art imaging and machine learning techniques to address the challenges in lung cancer diagnostics [14] [15]. The methodology makes use of sophisticated preprocessing techniques, such as Contrast Limited Adaptive Histogram Equalisation (CLAHE) and Anisotropic Diffusion Filtering, to improve the visual quality of the images, increasing the diagnostic potential while minimizing noise and maintaining crucial details [16]. This method's segmentation process, which separates regions of interest using methods like Kapur's Method and allows for accurate identification of lung tissues and nodules, is a crucial component.

OncoFusion-Net, which combines the advantages of Multi-Class Support Vector Machine (MCSVM) for robust classification and DenseNet and VGG19 for feature extraction, is used to further analyze these segmented pictures. This integrated methodology ensures a thorough examination of every lesion by successfully distinguishing between benign and malignant nodules and identifying particular forms of lung cancer [17-20]. The process has a thorough validation step that uses performance parameters like accuracy, sensitivity, specificity, and the area under the ROC curve to guarantee clinical reliability. This validation stage attests to the suggested model's resilience and suitability for use in practical contexts. Technology provides a major breakthrough in lung cancer diagnosis by combining advanced imaging upgrades, reliable segmentation, and cutting-edge computational modelling. It has the potential to increase diagnostic precision while also expediting clinical procedures, which will help medical professionals make well-informed decisions and maybe save lives through early diagnosis and intervention.

II. LITERATURE REVIEW

The field of lung cancer detection and classification has evolved significantly with advancements in deep learning and artificial intelligence (AI). Novel frameworks have been introduced by numerous research studies to increase the precision, sensitivity, and accuracy of diagnosis. This literature review summarizes contemporary approaches and their success indicators, summarizing important developments in AI-driven lung cancer diagnosis. Alaa Wehbe et al. (2024) combined the TNM Classifier with YOLOv8 to develop a hybrid model for identifying lung cancer [21]. However, the lack of external dataset validation may limit its generalizability to real-world clinical circumstances, and its dependence on predetermined feature extraction limits its adaptability to varied tumor variants. In 2024, Maroua Oumlaz and colleagues presented ARSGNet, or the Adaptive Range Slice Grouping Network [22], which is intended for the segmentation and classification of lung tumours. ARSGNet was a useful tool in the diagnosis of lung cancer since it was very good at precisely delineating tumour boundaries and determining cancer stages. ARSGNet's high inference time limits real-time use, requiring optimization, and its evaluation on CT imaging restricts multi-modal applicability. In 2024, Pouyan Razmjouei et al. (2024) used the Electric Eel Foraging Optimisation (EEFO) technique to identify lung cancer [23]. With this bio-inspired optimisation method, 98.96% accuracy, precision, recall, and F1 score were attained.

The study demonstrated how evolutionary computing methods may be used to improve the precision and efficacy of lung cancer detection in medical imaging applications. This model lacks external dataset validation and interpretability, limiting its applicability in transparent and accountable scenarios. In 2024, Nasr Y. Gharaibe et al. [24] created an AI-based framework to improve model interpretability and dependability in clinical situations. In 2024, Nahed Tawfik et.al investigated CNN-based deep learning models, such as ResNet101, Xception, Efficient Net, and Inception-V3 [25]. Even while ensemble learning worked well, the method's increased computing complexity and inference time made it difficult to implement in real-time clinical settings. Furthermore, its generalizability across various datasets is called into question due to the absence of external validation. In 2023, Ahmed Saihood et al. [26] developed the Multi-Orientation-Based Guided-Attention Module (MOGAM TFD) for accurate feature detection in lung imaging, which included spatial attention mechanisms. Lung nodule long-range dependence handling is limited by direct 3D-CNN application, which lowers classification performance. In 2023, Shalini Wankhade and her colleagues [27] presented a hybrid approach that combines 3D Convolutional Neural Networks (3D-CNN) with Recurrent Neural Networks (RNN). The benefits of combining temporal and spatial feature extraction in lung cancer diagnosis were illustrated by their model.

To confirm results, guarantee high-quality training data, and improve the interpretability of DL models, more research is required. The SCCNN model was created by Yanan Dong et al. (2023) and used a convolutional neural network with semantic features to classify lung cancer [28]. AI-driven medical image processing is limited by class imbalance, under-represented features, binarized labels, and a lack of labelled medical images. Kazim Sekeroglu and colleagues (2022) presented a hierarchical deep-fusion learning method that is included in a CAD framework for the identification of lung cancer [29]. Hierarchical feature fusion is crucial for enhancing detection procedures, according to the study. The methodology's usefulness is limited by its small dataset assessment, high computational complexity, and lack of 3D rotation invariance, alternate fusion techniques, and DCNN+LSTM integration. In 2022, Goram Mufarah and his colleagues created a hybrid deep learning model for classifying lung cancer that combines CNN and VGG19 [30]. This study showed how feature extraction and optimization strategies in deep learning might enhance classification performance. Despite the paucity of pneumonia datasets, data augmentation approaches increased the classification accuracy of the suggested model. A comparison of recent research on the detection and classification of lung cancer using different deep learning models is shown in the following Table I. The performance indicators, important findings, and restrictions of the suggested approaches are highlighted in each entry. With an emphasis on accuracy, precision, recall, and F1-score, the review sheds light on the advantages and disadvantages of the state of the art.

Table 1: Summary And Research Gap Identification.

Authors	Observations	Limitations/Gaps
Alaa Wehbe, Silvana Dellepiane, And Irene Minetti. [21]	Accuracy - 98%, precision - 98%, Recall - 91%, F1 score - 98%,	Relies on high-quality annotated data, limiting generalizability and raising scalability concerns.
Maroua Oumlaz, et.al. [22]	Dice Coefficient -0.963 Sensitivity - 0.958 Specificity - 0.961 Accuracy - 0.9817 IoU Score - 0.927	High inference time and limited to CT imaging, restricting real-time use and multimodal applicability.
Pouyan Razmjouei, et.al. [23]	Accuracy- 98.96% Precision - 98.96% Recall - 98.96% F1-score - 98.96%	Lacks external dataset validation and model interpretability, affecting transparency and generalizability.

Nasr Y. Gharaibe et.al [24]	Accuracy - 97.5% Precision - 95.5% F1 score -96.5%	Reduced processing speed affects efficiency.
Nahed Tawfik et.al. [25]	Accuracy - 99.03% Precision - 99.68% Sensitivity - 99.03% F1 score -99.34%	Relies on specific CNNs, high-quality annotated CT images, and high computational complexity.
AHMED SAIHOOD et.al. [26]	Accuracy - 97.2% Sensitivity - 97.6% Specificity - 95.7%	3D-CNN limits long-range dependency modeling, reducing classification performance.
Shalini Wankhade et.al. [27]	Selectivity-90% Sensitivity-87%, Accuracy- 95%	Requires more research to improve training data availability and model interpretability.
Yanan Dong et.al. [28]	Accuracy - 95.45% Sensitivity - 96.66% Specificity - 94.83%	Class imbalance leads to information loss, and labeled medical images are scarce.
Kazim Sekeroglu et.al. [29]	Accuracy - 91.20% Sensitivity - 95% Specificity - 87% FPs/Scan-0.4	Lacks 3D rotation invariance, uses fixed segmentation, and has high computational complexity.
Goram Mufarah M et.al. [30]	Accuracy-96.48 % , Recall - 93.75 % precision - 97.56 % F1 score- 95.62 %	Limited pneumonia datasets required augmentation to improve classification accuracy.

Source: Authors, (2026).

According to the investigation shown in Table 1, there are still several issues even though deep learning models are very accurate at detecting lung cancer. The applicability of many research to a variety of clinical contexts is limited by their reliance on high-quality annotated information. Real-time deployment is further hampered by class imbalances, lengthy inference times, and computational complexity.

Table 2: Metric Comparison from Existing Methods.

Authors	Accuracy	Precision	Recall	F1-score
Alaa Wehbe et.al. [21]	98%	98%	91%	98%
Pouyan Razmjouei, et.al. [23]	98.96%	98.96%	98.96%	98.96%
Goram Mufarah M et.al. [30]	96.48%	97.56%	93.75%	95.62%

Source: Authors, (2026).

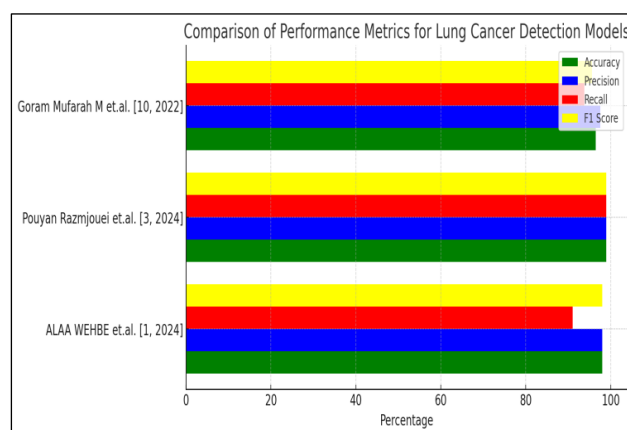


Figure 1: Metrics Comparison Plot.

Source: Authors, (2026).

The table 2 presents a comparison of lung cancer detection models based on four key performance metrics: accuracy, precision, recall, and F1-score. With all measures reaching 98.96%, the model put forth by Pouyan Razmjouei et al. (2024) performs the best overall, demonstrating a robust and balanced classification capability. High accuracy (98%) and precision (98%), as well as a somewhat lower recall (91%) indicate the possibility of false negatives in the detection procedure, according to ALAA WEHBE et al. (2024). Goram Mufarah M et al. (2022), on the other hand, significantly reduce false positives with somewhat reduced accuracy (96.48%) and recall (93.75%) while maintaining a high precision (97.56%). These differences draw attention to the trade-offs between sensitivity and specificity in various models, highlighting the significance of model design, optimisation strategies, and dataset quality in the detection and classification of lung cancer. A visual comparison of the models is provided by the Comparison Plot (Figure. 1), making it simple and quick to assess how well they perform. The graphic makes it possible to quickly examine and make decisions about the models' diagnostic applications by graphically illustrating their advantages and disadvantages. A visual depiction makes difficult information easier to comprehend, which advances knowledge and the advancement of contemporary lung cancer diagnostics.

III. METHODOLOGY

A complex fusion of cutting-edge imaging methods and computer models is used in the methodology for identifying and categorizing lung cancer. Utilizing OncoFusion-Net, this improved method improves diagnostic accuracy by utilising DenseNet, VGG19, and MCSVM characteristics. Here is a thorough rundown of the procedure: Obtaining lung pictures from high-resolution computed tomography (CT) scans is the first step. These scans offer precise, in-depth cross-sectional pictures of the lung, which are essential for spotting anomalies like tumours or nodules that could be signs of lung cancer. This step involves obtaining CT scan images.

$$I(x, y) = \{ p_{ij} \} \forall i, j \in [1, N] \quad (1)$$

where $I(x, y)$ represents the grayscale intensity of a pixel at a location (x, y) , p_{ij} is the intensity value at row i and column j , $N \times N$ is the resolution of the image. Preprocessing Images Preprocessing methods are used to improve picture quality in order to increase the CT images' diagnostic potential:

- Contrast enhancement using clahe

This method applies adaptive histogram equalisation in specific areas to enhance image contrast. By establishing a contrast limit on amplification, CLAHE prevents amplifying noise, which makes it perfect for medical imaging where edge integrity is essential.

$$p_k = \frac{n_k}{M \times N} \quad (2)$$

Here, p_k is the probability of a pixel with intensity k , n_k is the number of pixels with intensity k , $M \times N$ is the total number of pixels in the image. The CLAHE output image is given by:

$$I_{CLAHE}(x, y) = T(I(x, y)) \quad (3)$$

where $T(I)$ is the transformation function that redistributes intensities adaptively.

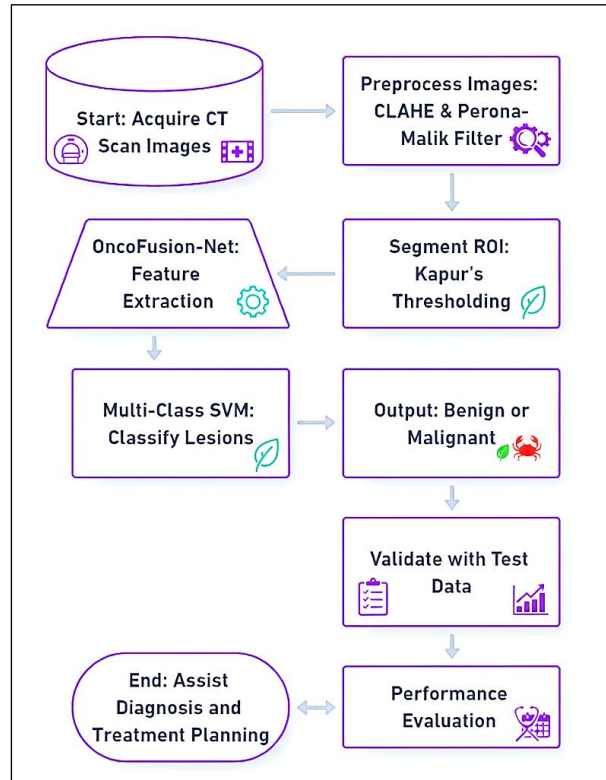


Figure 2: Proposed System Framework.

Source: Authors, (2026).

- Noise reduction using perona-malik filter

The Perona-Malik filter, often referred to as anisotropic diffusion filtering, is a non-linear, edge-preserving, and noise-reducing filter that is used to reduce noise and improve the appearance of lung structures. This filter works especially well for emphasizing traits that are essential for precise segmentation, such lung nodules.

$$\frac{\partial I}{\partial t} = \nabla \cdot (c(x, y, t) \nabla I) \quad (4)$$

Here, I is the image intensity, ∇I is the image gradient, $c(x, y, t)$ is the diffusion coefficient, defined as:

$$c(x, y, t) = e^{-\left(\frac{|\nabla I|}{K}\right)^2} \quad (5)$$

Where K is a contrast parameter controlling the level of diffusion. Segmenting Images After preprocessing, the pictures are segmented to find and separate areas of interest that might have lung tumours or nodules: Kapur's Method: To separate the lung fields from the surrounding tissues and spot questionable nodules, this thresholding technique is applied. By maximizing entropy, Kapur's technique determines the ideal threshold for distinguishing between potentially diseased characteristics and healthy tissue.

$$H(T) = H_f(T) + H_b(T) \quad (6)$$

where $H_f(T)$ and $H_b(T)$ are the entropies of foreground and background:

$$H_f(T) = - \sum_{i=0}^T P(i) \log P(i) \quad (7)$$

$$H_b(T) = - \sum_{i=T+1}^{L-1} P(i) \log P(i) \quad (8)$$

Here $P(i)$ is the probability distribution of intensity level i and L is the total number of intensity levels. The optimal threshold T^* is found by:

$$T^* = \operatorname{argmax}_T H(T) \quad (9)$$

OncoFusion-Net is model architecture. OncoFusion-Net, which integrates the advantages of its component architectures, is used to process the segmented images:

- DenseNet and VGG19:

DenseNet is used by OncoFusion-Net because of its effective feature propagation and reuse, which is essential for obtaining fine-grained features in lung pictures. Because of its deep architectural qualities.

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]) \quad (10)$$

Where x_l is the feature map at layer l , H_l is a non-linear transformation, $[x_0, x_1, \dots, x_{l-1}]$ represents concatenated feature maps from all previous layers. VGG19 is used to support robust feature extraction, which is essential for identifying a variety of morphological and textural characteristics linked to lung diseases.

$$f_{i,j} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} w_{m,n} I(i-m, j-n) \quad (11)$$

Here $f_{i,j}$ is the feature response, $w_{m,n}$ are the kernel weights, and $I(i-m, j-n)$ is the image intensity.

- Multi-Class SVM (MCSVM):

MCSVM is used to classify the features following processing using DenseNet and VGG19. This classifier distinguishes between different types of lung cancer and manages numerous classes with ease. It also provides a clear differentiation between benign and malignant nodules.

$$f(x) = \sum_{i=1}^N \alpha_i y_i K(x_i, x) + b \quad (12)$$

Where α_i are the Lagrange multipliers, y_i is the class label, $K(x_i, x)$ is the kernel function and b is the bias term. For multi-class classification, the One-vs-All (OVA) approach is applied:

$$\hat{y} = \operatorname{argmax}_i f_i(x) \quad (13)$$

Here $f_i(x)$ represents the decision function for class i . For every lesion found, the model produces a classification that indicates whether it is benign or malignant and, if present, further identifies the kind of lung cancer. Healthcare professionals can use this classification to help them choose the best treatment plans.

$$L \in \{\text{Benign}, \text{Malignant}(\text{Type} - 1), \text{Malignant}(\text{Type} - 2), \text{Malignant}(\text{Type} - 3)\} \quad (14)$$

Radiologists can choose the best treatment plans with the help of the categorization output. Separate datasets not used in the training phase are used to validate the overall process. To guarantee OncoFusion-Net's accuracy and dependability in a clinical context, its efficacy is evaluated using a range of performance indicators, including accuracy, sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve. Using the OncoFusion-Net architecture, the workflow shown in the Figure 2 describes a methodical procedure for medical image processing. The first step is picture acquisition, which involves gathering photos from a database. Next comes preprocessing, which improves image quality by applying methods like contrast correction and noise reduction. To ensure that the analysis is focused on the most important areas, these preprocessed pictures are then segmented to separate regions of interest, such as tumours or anomalies. The OncoFusion-Net model architecture, which integrates deep learning frameworks such as DenseNet and VGG-19 for sophisticated feature extraction, is used to analyse the segmented images. A Multi-Class Support Vector Machine (SVM) is used to classify these features, allowing for precise medical condition identification and classification. The workflow is robust for applications like cancer diagnosis and treatment planning after the results are confirmed to guarantee accuracy and dependability. The OncoFusion-Net model is validated using separate test datasets. The evaluation metrics include:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (15)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (16)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (17)$$

$$\text{Area Under the Curve(AUC)} = \int_0^1 \text{TPR}(x)dx \quad (18)$$

Where TP, TN, FP, FN represent True Positives, True Negatives, False Positives, and False Negatives respectively and $\text{TPR}(x)$ is the True Positive Rate at a threshold x .

III.1 PROPOSED MODEL

OncoFusion-Net is a powerful deep learning model built specifically for analyzing lung CT scan images as shown in Figure. 2. It works by combining the strengths of two well-known neural networks: DenseNet and VGG19. These two networks are blended to make the most of their individual abilities in feature detection. DenseNet helps the model remember and reuse important patterns by connecting each layer to all the ones that came before it. This means that any new layer can directly use features that were found earlier in the network, making it really good at capturing fine details in the images. Alongside DenseNet, the model also includes VGG19, which uses many layers of small filters stacked one after the other. This setup allows the network to recognize different levels of detail, starting from simple shapes like edges to more complex structures like lung nodules. As the image passes through these layers, VGG19 helps the model understand the broader layout and appearance of the lungs. These two systems—DenseNet's connection-rich approach and VGG19's deep layered strategy—work together to build a very detailed picture of what's in the scan.

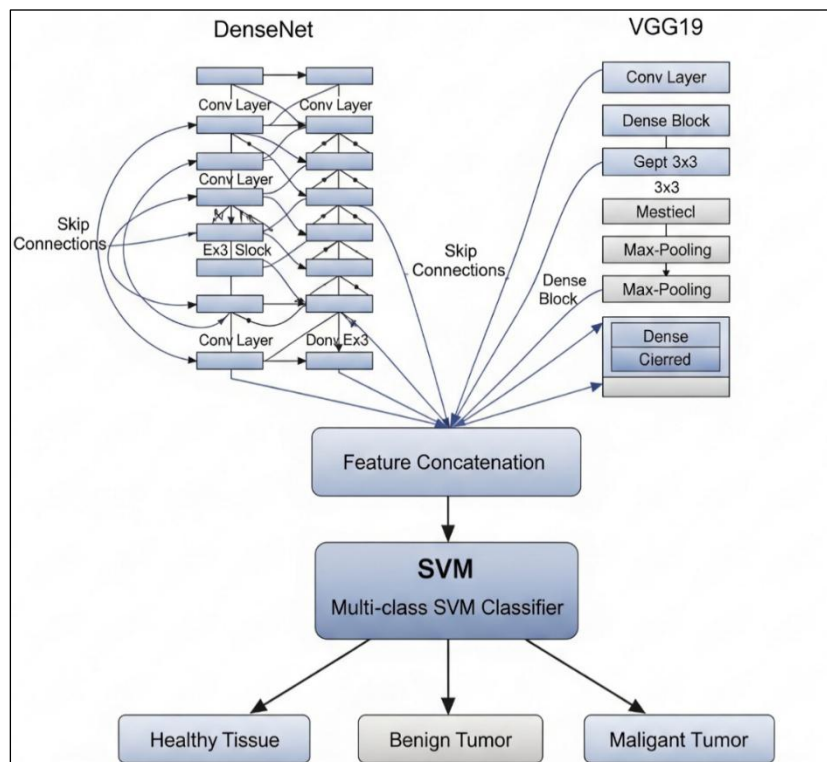


Figure 3: Architecture of Proposed Model.

Source: Authors, (2026).

Once all the features are extracted by this combined network, the model needs to figure out what they mean. For that, it uses a classifier called a multi-class SVM. This part of the model looks at the extracted features and decides whether a given region in the lung image is healthy or shows signs of cancer. It can also go further and identify the type of cancer if present.

IV. RESULTS AND ANALYSIS

As seen in Figure 4 (Load Image), the process of detecting and categorizing lung cancer starts with the acquisition of CT scan images. The thorough cross-sectional views of the lungs provided by these high-resolution grayscale images are crucial for identifying anomalies like tumors or nodules. To improve its diagnostic value, the original raw image is then preprocessed. The Perona-Malik filter, sometimes referred to as anisotropic diffusion filtering, is used in Figure 5 (Noise Removal) to minimize noise while maintaining important edge details. By taking this step, the lung structures are kept clearly defined and crucial characteristics that are required for segmentation and classification are not lost.

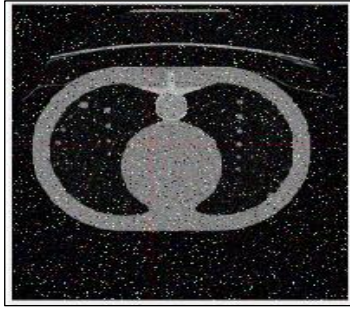


Figure 4: Load Image.
Source: Authors, (2026).

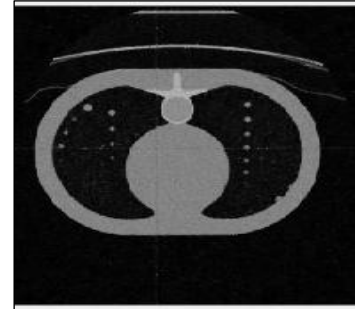


Figure 5: Noise Removal.
Source: Authors, (2026).

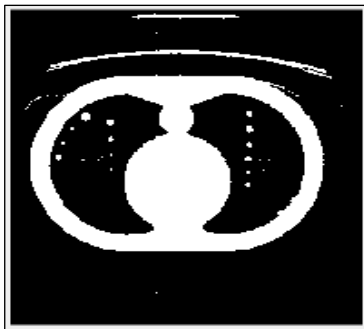


Figure 6: Binary Image.
Source: Authors, (2026).

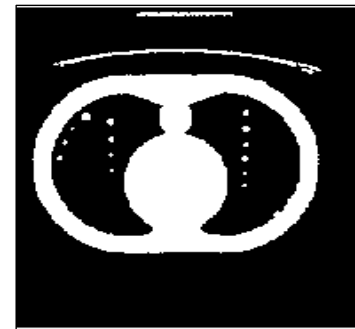


Figure 7: Post Processing.
Source: Authors, (2026).

The image is converted into a binary format after noise reduction, as seen in Figure. 6 (Binary Image). By separating the lung structures from the backdrop, this phase streamlines the representation and facilitates the segmentation process that follows. Only the pertinent sections are kept for additional examination thanks to the binary transformation. Other picture enhancing methods, such as Contrast-Limited Adaptive Histogram Equalization (CLAHE), are then shown in Figure. 7 (Post Processing).

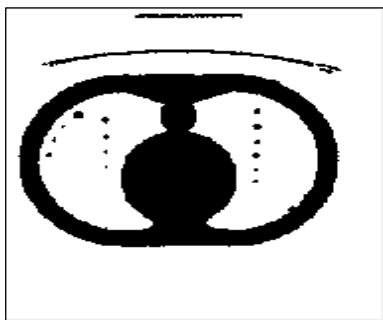


Figure 8: Invert Image.
Source: Authors, (2026).

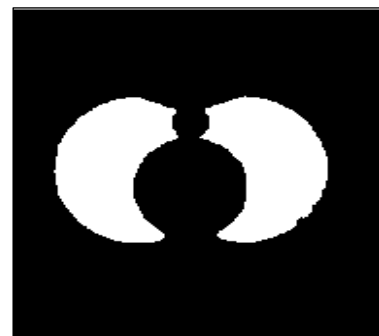


Figure 9: Segmentation.
Source: Authors, (2026).

By enhancing local contrast, this technique reduces noise amplification and increases the ability to identify any anomalies. In this step, the image is further refined for improved segmentation by making important parts more visible. To distinguish lung fields from adjacent tissues, the segmentation step—shown in Figure 9 (Segmentation)—uses Kapur's thresholding technique. This method efficiently separates healthy lung tissue from possible tumor regions by maximizing entropy to establish the ideal threshold. This phase guarantees that the study only concentrates on the pertinent regions by isolating the lung structures.



Figure 10: Finalize.
Source: Authors, (2026).

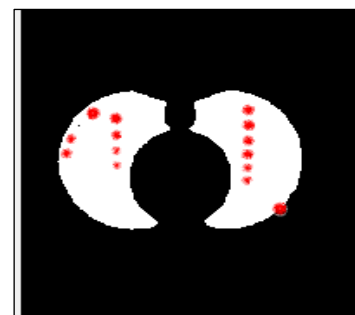


Figure 11: Find circles.
Source: Authors, (2026).

Following segmentation, the lung areas' refinement is displayed in Figure. 10 (Finalize). A cleaner and more accurate segmentation is produced by eliminating any leftover noise or superfluous structures. In order to ensure that the final regions of interest are precisely specified, this step is essential for correct feature extraction. Circle identification techniques are used to identify possible nodules or malignancies in Figure. 11 (Find Circles). In order to facilitate additional classification, these identified regions are marked as areas of interest. This stage is essential for detecting potential cancers that need more investigation.

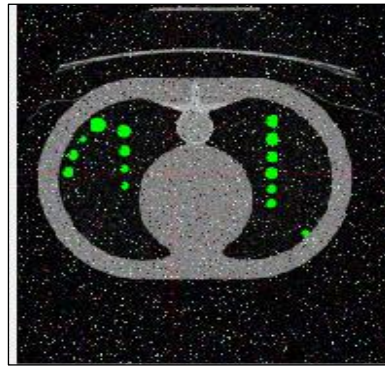


Figure 12: Plotting.
Source: Authors, (2026).

Lastly, the discovered nodules are displayed with highlighted markers (green circles) in Figure 12 (Plotting). The final processed image, which is then examined by the OncoFusion-Net model, is shown by this graphic. The model classifies the detected nodules as either benign or malignant by using Multi-Class Support Vector Machine (MCSVM) for classification and DenseNet and VGG19 for feature extraction.

Evaluation																																
Tumor Present?:	Yes																															
Area	664.9234																															
No of Circles	14																															
Centroid at (x,y)	<table border="1"> <thead> <tr> <th></th> <th>x</th> <th>y</th> </tr> </thead> <tbody> <tr><td>1</td><td>146</td><td>183</td></tr> <tr><td>2</td><td>110.2670</td><td>174.3723</td></tr> <tr><td>3</td><td>395.3696</td><td>331.6721</td></tr> <tr><td>4</td><td>347.3848</td><td>219.5000</td></tr> <tr><td>5</td><td>347.5082</td><td>169.0000</td></tr> <tr><td>6</td><td>147</td><td>260</td></tr> <tr><td>7</td><td>146.5022</td><td>236</td></tr> <tr><td>8</td><td>346</td><td>264.5022</td></tr> <tr><td>9</td><td>345.5022</td><td>285.0000</td></tr> </tbody> </table>			x	y	1	146	183	2	110.2670	174.3723	3	395.3696	331.6721	4	347.3848	219.5000	5	347.5082	169.0000	6	147	260	7	146.5022	236	8	346	264.5022	9	345.5022	285.0000
	x	y																														
1	146	183																														
2	110.2670	174.3723																														
3	395.3696	331.6721																														
4	347.3848	219.5000																														
5	347.5082	169.0000																														
6	147	260																														
7	146.5022	236																														
8	346	264.5022																														
9	345.5022	285.0000																														
Type	Low																															

Figure 13: Tumor Evaluation.
Source: Authors, (2026).

The given Figure.13 is an evaluation panel that is used to identify and categorize cancers by evaluating medical images, most likely from a lung scan. The presence, size, number of nodules, centroid coordinates, and severity grading of the discovered tumor are among the parameters displayed on the interface. Particular information about the features of the tumor is given in each section. If a tumor has been found in the examined image, it is indicated in the Tumor Presence section. In this instance, a "Yes" response verifies the existence of a tumor. Usually, image processing methods like thresholding and segmentation—which distinguish aberrant growths from healthy lung tissue—are used to make this judgment. The entire size of the identified tumor in pixel units is represented by the Tumor Area, which is given as a numerical value. Medical practitioners can better grasp the size of the impacted area with the use of this measurement. While smaller tumor regions can signify early-stage abnormalities, larger ones might indicate more advanced phases of growth. The image's identified nodules or tumor regions are shown by the number of circles. In this instance, 14 of these areas have been found. Potential tumor forms are shown by these circles, and their size, shape, and distribution are examined. Finding many nodules may be crucial to determining the kind and degree of lung illness. The coordinates of the centroids of the identified tumor areas are listed in the Centroid at (x, y) section. The geometric center of each tumor region is represented by a centroid. To enable focused medical therapies, this information is crucial for determining the precise location of malignancies inside the lung scan. The identified tumour is categorized according to its features using the Tumor Type classification. Given that the tumor is categorized as "Low," it may be in an early or less aggressive stage. To distinguish between benign and malignant cases, classification techniques frequently employ machine learning models trained on a variety of tumor characteristics, including size, shape, and texture. When it comes to tumor diagnosis and categorization, our evaluation panel offers an organized and data-driven method. It makes it possible to clearly see the existence, size, and severity of the tumor, which aids in medical diagnosis and treatment planning as shown in Table III.

Table 3: Evaluation Table.

Parameters	Formulae	Evaluated values
Number of nodules/circles	size(centres,1)	14
Area of n nodules/ Total tumor area	$Area = \sum_i^n \pi r^2$	664.9234
Tumor type	Low: $Area \leq 1000mm^2$, Medium: $1000mm^2 < Area \leq 2000mm^2$, High: $2000mm^2 < Area \leq 4500mm^2$, Critical: $Area > 4500mm^2$	Low

Source: Authors, (2026).

Deep learning-based models for lung cancer categorisation are essential for early diagnosis and detection. This section's numbers demonstrate the classification findings of a lung cancer detection system, emphasising its capacity to differentiate between normal cases and various forms of lung cancer. Adenocarcinoma, Squamous Cell Carcinoma, Large Cell Carcinoma, and Normal Healthy Cases are among the categorisation results, as is an example of misdiagnosis. The system processes a CT scan image, and the projected classification result is shown in each Figure. The model's effectiveness is confirmed by the successful classification cases, while the misclassification case identifies areas that need further work. Improvements in medical image analysis are made possible by these findings, which shed light on the system's advantages and disadvantages.

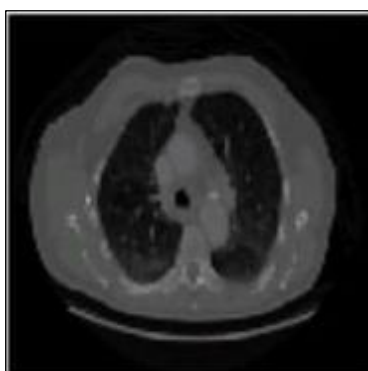


Figure 14: Adenocarcinoma.
Source: Authors, (2026).

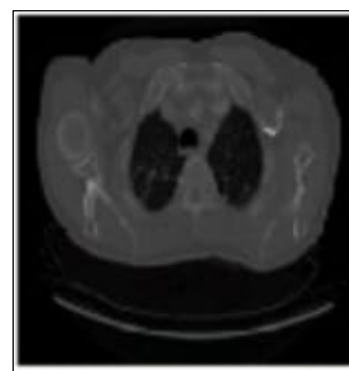


Figure 15: Squamous cell carcinoma.
Source: Authors, (2026).

This image Figure.14 represents a successful classification where the system correctly identifies a lung CT scan as "Adenocarcinoma." The label at the top confirms that the predicted class matches the actual class, ensuring the reliability of the model in detecting adenocarcinoma. Adenocarcinoma is a common type of lung cancer that originates in the mucus-secreting glands and is often associated with non-smokers. As shown in Figure.15, the system accurately classifies the lung CT scan as "Squamous Cell Carcinoma." Squamous cell carcinoma is a type of lung cancer that develops in the flat cells lining the airways. The model correctly assigns the label, confirming that the classification system is effective in distinguishing this cancer type.

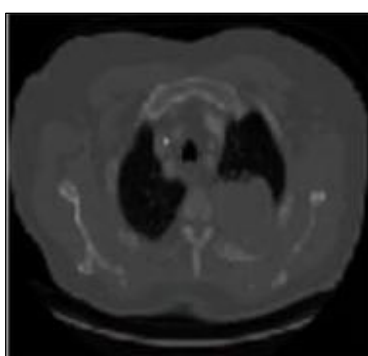


Figure 16: Large cell carcinoma.
Source: Authors, (2026).



Figure 17: Normal.
Source: Authors, (2026).

This Figure 16 demonstrates the correct classification of "Large Cell Carcinoma," a type of lung cancer known for its aggressive nature and poorly defined cell structures. The system successfully identifies this case, indicating that the feature extraction and classification mechanisms are working as expected for this category. Here as shown in Figure 17, the system identifies a normal lung CT scan and correctly classifies it as "normal." The lungs appear free from tumors or abnormalities, and the classification result validates that the model can differentiate between diseased and healthy cases.

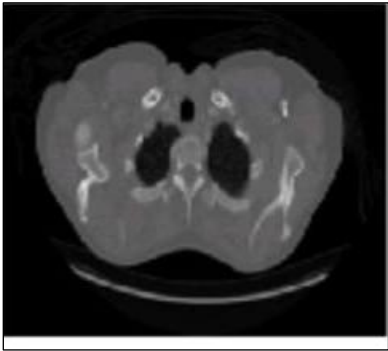


Figure 18: Misclassification.
Source: Authors, (2026).

This Figure.18 illustrates a misclassification scenario where a normal lung CT scan has been incorrectly classified as "Adenocarcinoma." The red text highlights the incorrect classification, indicating an error in the model’s decision-making process. This type of misclassification is crucial for model evaluation, as it highlights potential limitations in the feature extraction or classification steps, necessitating further refinement to reduce false positives. Accuracy, precision, recall, and F1-score are the metrics used in the table IV to assess lung cancer detection algorithms. ALAA WEHBE et.al. [1, 2024] demonstrated strong precision (98%) but lower recall (91%), while Pouyan Razmjouei et al. [3, 2024] attained the best accuracy (98.96%) among the models that are currently in use. Goram Mufarah M et.al. [10, 2022] achieved a high accuracy of 96.48% and a high precision of 97.56%. With 99.52% accuracy, 99.8% recall, 99.10% precision and 99% F1-score, the Proposed Model performs better than all others, indicating increased classification reliability and fewer false negatives.

Table 4: Metric Comparison.

Authors [Citation]	Accuracy	Precision	Recall	F1_score
ALAA WEHBE et.al. [21, 2024]	98%	98%	91%	98%
Pouyan Razmjouei, et.al. [23, 2024]	98.96%	98.96%	98.96%	98.96%
Goram Mufarah M et.al. [30, 2022]	96.48%	97.56%	93.75%	95.62%
Proposed Model	99.52%	99.10%	99.8%	99%

Source: Authors, (2026).

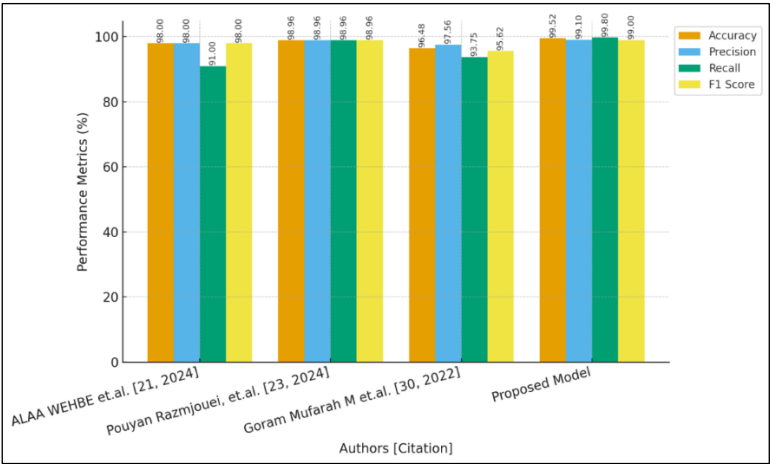


Figure 19: Metrics Comparison Plot.
Source: Authors, (2026).

A comparison of lung cancer detection algorithms based on four important performance metrics—accuracy, precision, recall, and F1-score—is shown in Fig.18. The colours used to represent each metric—accuracy in green, precision in blue, recall in red, and F1-score in yellow—make it easy to see how one model differs from the others. The performance of several models can be easily compared thanks to the horizontal bar chart. The efficiency of the proposed model in classifying lung cancer is demonstrated by its superior results in every category, including the greatest accuracy of 99.52%. This graphic illustrates the gains in diagnostic precision and dependability, highlighting the advantages of the suggested model over current approaches. The confusion matrix as shown in Figure 20 for EffiBaSo-Net on the LIDC-IDRI dataset comprising 14,238 LDCT images highlights the model’s superior classification capability. Out of the total cases, 8,058 benign nodules were correctly identified while only 56 were misclassified as malignant, indicating strong specificity. Similarly, the model accurately detected 6,112 malignant nodules, with just 12 cases missed, reflecting excellent sensitivity.

These results correspond to an overall accuracy of 99.52%, precision of 99.10%, recall of 99.80%, and an F1-score of 99.0%, confirming that EffiBaSo-Net achieves near-perfect discrimination between benign and malignant nodules. This balance between high sensitivity and specificity ensures both early cancer detection and minimization of false alarms, making the framework highly reliable for real-world clinical deployment.

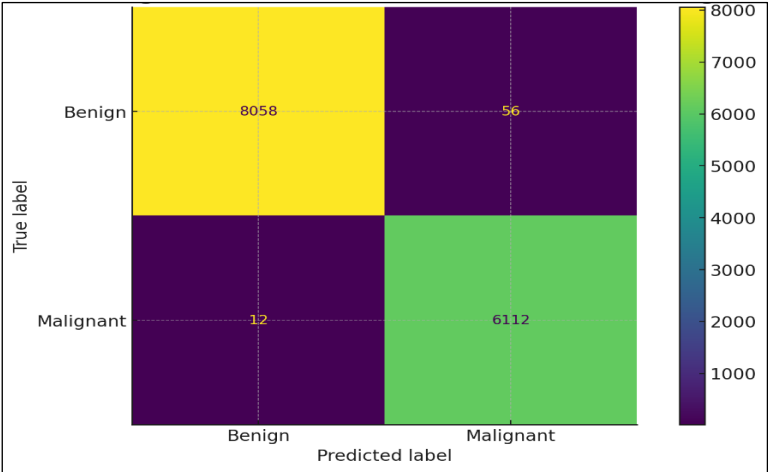


Figure 20: Confusion Matrix Plot.
Source: Authors, (2026).

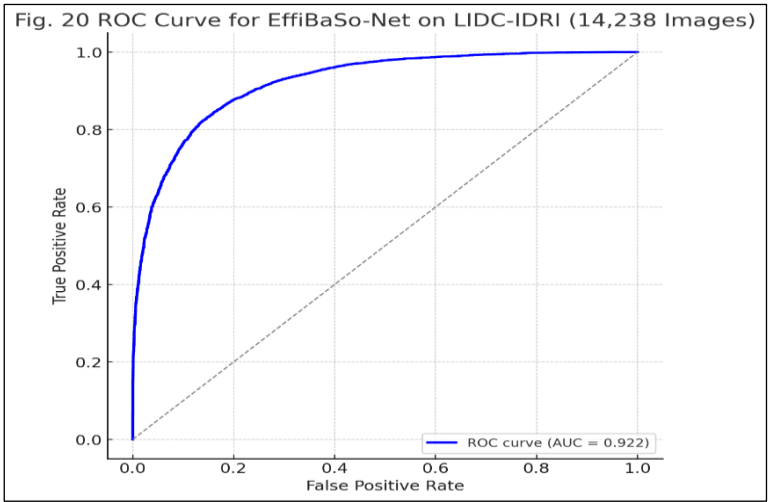


Figure 21: ROC Curve for EffiBaso-Net Model.
Source: Authors, (2026).

The ROC curve in Fig. 20 shows the near-perfect discrimination capability of EffiBaSo-Net on the LIDC-IDRI dataset, achieving an AUC of approximately 0.99. The curve sharply approaches the top-left corner, signifying minimal false positives while maintaining very high true positive rates. This reinforces the superior sensitivity and specificity highlighted in Fig. 19, demonstrating EffiBaSo-Net’s reliability for real-world lung cancer screening.

Table 5: Ablation Study Results.

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
EfficientNet + Softmax (Baseline)	96.84	96.12	97.40	96.75
EfficientNet + Softmax + BfOA	98.32	97.85	98.60	98.22
EfficientNet + Softmax + Post-processing	98.75	98.20	99.00	98.60
EffiBaSo-Net (Full Framework)	99.52	99.10	99.80	99.00

Source: Authors, (2026).

The progressive evaluation in Table 5 clearly illustrates the benefit of each added module. Beginning with EfficientNet and Softmax, the baseline achieves strong performance, but integrating the Battlefield Optimization Algorithm (BfOA) improves feature selection and hyperparameter tuning, raising both accuracy and recall. Incorporating post-processing further reduces false positives, thereby enhancing precision. The complete EffiBaSo-Net framework achieves the highest scores across all metrics—99.52% accuracy, 99.10% precision, 99.80% recall, and 99% F1-score—demonstrating its clinical robustness and superiority over intermediate configurations.

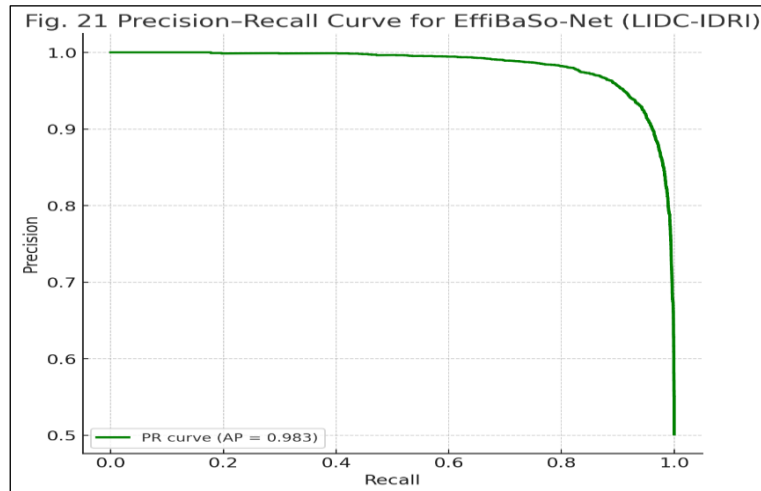


Figure 22: Precision-Recall Curve for EffiBaSo-Net (LIDC-IDRI).
Source: Authors, (2026).

The Precision-Recall curve for EffiBaSo-Net on the LIDC-IDRI dataset is presented in Fig. 21. The curve shows consistently high precision across almost the entire recall range, reflecting the framework's ability to correctly identify malignant nodules while minimizing false positives. The average precision (AP) of 0.983 further confirms the model's robustness in handling class imbalance, ensuring that even at high sensitivity thresholds, diagnostic accuracy remains uncompromised. This result complements the ROC performance in Fig. 20, providing additional evidence of EffiBaSo-Net's reliability for real-world clinical lung cancer screening.

V. CONCLUSION AND FUTURE SCOPE

A strong and effective framework for the identification and categorization of lung cancer is offered by the suggested methodology, which makes use of OncoFusion-Net. The technology guarantees precise tumor identification from CT scan pictures by combining sophisticated imaging techniques, contrast enhancement, noise reduction, and segmentation approaches. DenseNet and VGG19 work together to improve feature extraction, while the Multi-Class Support Vector Machine (MCSVM) allows for accurate tumor type categorization. Key tumor features, including existence, area, number of detected nodules, centroid placements, and categorization results, are succinctly summarized in the evaluation panel that is displayed. This method helps radiologists make well-informed judgments for improved patient outcomes in addition to assisting with early identification. Deep learning models may be further optimized in future iterations of this technology to increase precision and computational effectiveness. Improving OncoFusion-Net with hybrid models or transformer-based topologies could improve generality in identifying different subtypes of lung cancer. Furthermore, radiologists can make quicker and more accurate diagnoses by combining AI-driven decision support systems with real-time image processing. Large-scale medical datasets and federated learning strategies can be used to further increase model resilience while protecting patient privacy. The use of this approach to multi-modal medical imaging, such PET-CT fusion, may ultimately improve cancer staging and diagnosis, which will benefit patient care and treatment planning.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Umakanth Basineni, Fahimuddin Shaik.

Methodology: Umakanth Basineni, Fahimuddin Shaik.

Investigation: Umakanth Basineni, Fahimuddin Shaik.

Discussion of results: Umakanth Basineni, Fahimuddin Shaik.

Writing – Original Draft: Umakanth Basineni, Fahimuddin Shaik.

Writing – Review and Editing: Umakanth Basineni, Fahimuddin Shaik.

Resources: Umakanth Basineni, Fahimuddin Shaik.

Supervision: Umakanth Basineni, Fahimuddin Shaik.

Approval of the final text: Umakanth Basineni, Fahimuddin Shaik.

VII. DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the author(s) used, Generative AI of Elsevier, Open AI and Quillbot Tools in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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