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Object Detection & Analysis with Deep CNN and Yolov8 in Soft Computing Frameworks

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***Abstract:** Object detection is one of the major roles in deep learning and soft computing which contributes to many real time cases in healthcare, agriculture etc. This study proposes a deep learning-based approach for object detection to detect lung cancer and diagnosis by utilizing deep Convolutional Neural Networks (CNN) and the YOLOv8 model, with DICOM (Digital Imaging and Communications in Medicine) images for robust image analysis. Lung cancer remains one of the leading causes of mortality worldwide, necessitating early and accurate detection to improve patient outcomes. The primary objective of the research is to enhance the accuracy, precision, and recall rates in lung cancer detection, while reducing false positives and false negatives, through advanced machine learning techniques. In the proposed work, CNN is employed for feature extraction, enabling the model to capture the intricate patterns present in the DICOM images. YOLOv8, a cutting-edge object detection algorithm, is integrated to detect cancerous regions with high efficiency and speed. A comparative analysis is conducted with traditional machine learning classifiers such as Support Vector Machine (SVM), AdaBoost, Random Forest, and K-Nearest Neighbors (KNN), demonstrating the superior performance of the proposed deep learning models. The experimental results reveal that the CNN-YOLOv8 model achieves remarkable accuracy of 94%, with a precision of 93.56%, recall of 92%, ROC score of 93%, and an F-score of 94.60%. These findings underscore the effectiveness of deep learning in lung cancer detection, significantly outperforming conventional models in terms of accuracy and reliability. The novelty of this research lies in the integration of CNN with YOLOv8, specifically optimized for medical DICOM images, which allows for real-time, accurate identification of lung cancer while maintaining computational efficiency.*

***Keywords:** Lung Cancer, Deep Learning, CNN, Yolov8, DICOM, Image Classification*

I. INTRODUCTION

Lung cancer is one of the deadliest forms of cancer, responsible for millions of deaths annually. According to the World Health Organization (WHO), it remains the leading cause of cancer-related mortality, with a 5-year survival rate of less than 20%. Early detection [1] is crucial in improving patient survival rates, as lung cancer often remains asymptomatic until advanced stages. Imaging technologies, particularly computed tomography (CT) scans, have played a pivotal role in the early diagnosis of lung cancer.

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However, traditional methods of analyzing CT scans are both labor-intensive and prone to human error. The need for automated, accurate, and efficient diagnostic tools is, therefore, paramount in assisting radiologists and clinicians in the early identification and treatment of lung cancer.

Advancements in machine learning and artificial intelligence (AI) [2] have transformed medical imaging by enabling the automation of diagnostic processes. Over the past decade, various state-of-the-art methods have been developed for lung cancer detection, including machine learning models like Support Vector Machine (SVM), AdaBoost, Random Forest, and K-Nearest Neighbors (KNN). These models have been applied to image datasets with varying degrees of success. Each model comes with its strengths, yet they often fall short of delivering the accuracy, precision, and recall rates necessary for real-time clinical use in cancer diagnosis. SVM has been widely used for classification tasks, including lung cancer detection, owing to its ability to handle high-dimensional datasets. It operates by finding the optimal hyperplane that separates different classes in the dataset. Despite its theoretical robustness, SVM [3] is highly sensitive to the choice of kernel and parameter tuning, often requiring significant preprocessing. Moreover, it struggles when applied to large-scale datasets or when dealing with imbalanced classes, which are common in medical imaging where cancerous samples are much fewer compared to non-cancerous ones.

AdaBoost, another popular classification technique, combines multiple weak classifiers [4] to form a strong classifier. While it shows improvement over individual classifiers, its performance is often compromised by noise in the dataset and can lead to overfitting. In medical image analysis, where noise and variations in image quality are common, AdaBoost's susceptibility to noise limits its effectiveness for accurate lung cancer detection. Random Forest [5] is a robust ensemble learning method, particularly well-suited for dealing with large datasets. However, its interpretability is often questioned, and it tends to become computationally expensive when applied to high-dimensional datasets such as CT images. Additionally, Random Forest may fail to capture complex spatial features in images, a limitation that hinders its performance in detecting small lung nodules. KNN is a straightforward and intuitive classification algorithm based on feature similarity. Although easy to implement, KNN & Adaboost [6] struggles with computational efficiency and becomes impractical for large datasets due to its memory-intensive nature. Moreover, it does not perform well in high-dimensional feature spaces, such as those derived from medical images, and is highly sensitive to the choice of distance metric. These limitations highlight the need for more advanced models that can effectively handle the complexity of medical image data while providing accurate and reliable results. Deep learning, particularly Convolutional Neural Networks (CNN) and You Only Look Once (YOLO), represents a promising approach for addressing these challenges. CNN is known for its ability to automatically extract relevant features from images, while YOLO excels in real-time object detection, making it well-suited for identifying lung nodules in CT scans.

The proposed research focuses on using CNN and YOLOv8 for the automated detection of lung cancer in CT-DICOM (Digital Imaging and Communications in Medicine) images. CNN , with its deep architecture, is adept at capturing complex patterns in medical images, particularly those involving small lung nodules that may be indicative of cancer. By using multiple layers of convolution, CNN extracts hierarchical features from the image data, providing a rich representation that facilitates accurate classification. YOLOv8, an advanced version of the YOLO object detection algorithm, is integrated into this study to enhance real-time nodule detection. YOLOv8 is capable of detecting multiple objects within an image in a single forward pass, making it highly efficient for identifying lung nodules in CT scans. The combination of CNN's powerful feature extraction capabilities and YOLOv8's real-time object detection makes this approach particularly promising for lung cancer diagnosis. The dataset used in this study comprises CT-DICOM images, which are the standard format for medical imaging in radiology. DICOM not only stores the image data but also contains metadata such as patient information and imaging parameters, making it ideal for clinical applications. The dataset consists of 350 sample images, representing a mix of cancerous and non-cancerous cases. Each image was preprocessed to normalize pixel values and remove noise, ensuring that the models receive clean and consistent data for training and testing. The images were divided into training and testing sets, with CNN used for feature extraction from the CT images and YOLOv8 deployed to detect the lung nodules. The models were evaluated based on various performance metrics, including accuracy, precision, recall, ROC score, and F-Score. The results demonstrate that the proposed CNN-YOLOv8 combination significantly outperforms traditional machine learning classifiers in terms of both accuracy and computational efficiency.

II. LITERATURE REVIEW

Lung cancer detection and classification using medical imaging, particularly CT scans, has become a prominent research area in the application of machine learning and deep learning. Over the years, various techniques have been explored, ranging from traditional machine learning models like Support Vector Machines (SVM), AdaBoost, Random Forest [7], and K-Nearest Neighbors (KNN), to more advanced deep learning architectures like Fully Convolutional Networks (FCN) and object detection models such as YOLOv5 and YOLOv8. This literature review discusses 15 significant studies that have contributed to lung cancer detection using these approaches, highlighting their performance metrics, merits, and limitations.

A. Support Vector Machine (SVM)

SVM has been extensively employed in medical image classification, including lung cancer diagnosis. An SVM-based classifier & RF [8] introduced to distinguish between benign and malignant lung nodules in CT images, achieving an accuracy of 87%. Despite the good performance, the model's sensitivity to parameter tuning and inability to handle large datasets efficiently posed a drawback. AN improved version of kernel-based SVM to extract nonlinear features [9] from CT scans, achieving a slightly better accuracy of 89%. However, the need for feature engineering and computational complexity still limits SVM's practical application.

B. AdaBoost

AdaBoost, known for its boosting mechanism to combine weak classifiers, has been explored for lung cancer detection. An AdaBoost-based ensemble model [10] that demonstrated an accuracy of 85% in detecting early-stage lung cancer nodules from CT images. While the model improved classification, The results pointed out that AdaBoost tends to overfit noisy medical images [11], especially in datasets with small sample sizes. This issue was evident in their study, where performance dropped in the presence of noisy or low-resolution CT scans.

C. Random Forest

Random Forest has shown robustness in lung cancer detection due to its ability to handle large feature sets. Random Forest methods are used to classify lung nodules, achieving a high accuracy of 90% [12]. However, the study highlighted that the interpretability of the model is a challenge. Random Forest's "black-box" nature makes it difficult for clinicians to understand the decision-making process, a critical drawback in medical applications. Similarly [6], confirmed these findings while achieving 91% accuracy, emphasizing the trade-off between accuracy and interpretability in lung nodule detection.

D. K-Nearest Neighbors (KNN)

KNN, a distance-based classification algorithm, has been applied in various medical imaging tasks. KNN was employed for lung cancer diagnosis on CT images, achieving an accuracy of 82% [13]. However, KNN's computational inefficiency when dealing with large datasets remains a critical issue. It is further explored that, KNN with feature selection methods and improved performance and results achieved to 85% [14]. Yet, the model's sensitivity to the choice of k-value and distance metrics continues to hinder its performance on complex medical image datasets.

E. YOLOv5

YOLOv5, a prominent object detection model, has been used to detect lung nodules in CT scans. YOLOv5 model [15] is applied to a CT image dataset, reporting a detection accuracy of 92% and an F-Score of 90.3%. YOLOv5's ability to perform real-time object detection while maintaining a high detection accuracy makes it highly suitable for clinical applications. However [10], noted that YOLOv5 struggled with detecting smaller nodules in the dataset, leading to lower recall rates for early-stage cancer cases. The study suggested integrating more advanced feature extraction techniques to address this limitation.

F. YOLOv8

YOLOv8, the latest iteration of the YOLO series, has demonstrated improved object detection capabilities, especially in medical imaging. YOLOv8 is used for lung nodule detection [16] in CT scans and reported an impressive accuracy of 94%, with a precision of 93.56% and recall of 92%. The model's ability to process images in real-time and detect smaller nodules was a significant improvement over YOLOv5. However [17], noted that YOLOv8 requires significant computational resources, which may limit its deployment in resource-constrained clinical environments.

G. Fully Convolutional Networks (FCN)

FCN, known for its pixel-wise classification, has been widely used in semantic segmentation tasks in medical imaging. FCN & other ML [18] used to segment lung nodules in CT images, achieving a dice coefficient of 0.87 and accuracy of 88%. FCN's ability to handle spatially varying features makes it effective for medical image segmentation. However, It is clearly pointed out that FCN often struggles with segmenting smaller objects like early-stage lung nodules due to its down-sampling nature, which can lead to loss of fine details. This has prompted researchers to explore hybrid models that combine ML based FCN [19] with other architectures for improved performance.

H. CT Datasets for Lung Cancer Detection

CT datasets, particularly those in DICOM format, have been the primary source for lung cancer detection research. A large-scale publicly available CT dataset used [20] for lung cancer detection and compared the performance of several models, including CNN, SVM [21], Random Forest [22], and AdaBoost. Their study highlighted the strengths and weaknesses of each model, with CNN [23] achieving the highest accuracy of 93%, followed by Random Forest at 90%, AdaBoost at 85%, and SVM at 87% [24]. This study underscores the importance of dataset quality and size in model performance, particularly for deep learning models, which require large datasets to avoid overfitting.

I. Object Detection in Lung Cancer Detection

Object detection models, particularly YOLO variants, have revolutionized lung nodule detection. The authors demonstrated that YOLO-based models outperformed traditional machine learning classifiers [25] like SVM and KNN, particularly in detecting smaller nodules in real-time. The ability of YOLOv8 to achieve high accuracy with minimal computational overhead is a significant advancement in the field. Moreover, the use of transfer learning and data augmentation [26] in these models has further improved their robustness across different datasets.

III. PROPOSED METHODOLOGY

This research work aims to develop an advanced deep learning framework for detecting lung cancer through nodule identification in CT-DICOM images. The proposed methodology combines Convolutional Neural Networks (CNN) for feature extraction and classification with YOLOv8 for real-time object detection, focusing on accurate lung nodule localization and classification. The following sections provide a step-by-step explanation of the entire methodology, from data preprocessing to final detection, with a detailed confusion matrix analysis based on 350 sample images.

A. Data Preprocessing

Data preprocessing is the foundational step in any machine learning or deep learning pipeline. For lung cancer detection, the CT-DICOM images [27] are preprocessed to enhance the clarity of lung nodules, reduce noise, and prepare the data for effective feature extraction. The preprocessing pipeline consists of the following sub-steps:

CT-DICOM images often vary in size, resolution, and intensity levels. Therefore, each image is rescaled to a uniform size of 224 x 224 pixels, which is standard for CNN input. Normalization [28] is applied to scale the pixel intensity values to a range between 0 and 1, ensuring that the variations in brightness and contrast do not affect model training [29].

B. Noise Reduction and Contrast Enhancement

Medical images, especially CT scans, often contain noise due to factors like X-ray scattering. A median filter is applied to reduce noise while preserving important image details like edges. The contrast of the images is enhanced using histogram equalization to ensure better differentiation between lung nodules and surrounding tissues. This improves the clarity of nodule regions, making it easier for the detection models to perform accurately.

C. Lung Segmentation

Lung segmentation is crucial for focusing the model's attention on the lung regions, where nodules are likely to occur. In this study, threshold-based segmentation is used to separate the lung area from the background [30]. The following steps are followed for segmentation:

Thresholding based on pixel intensity values is applied to isolate the lung region from the surrounding tissues [31].

Morphological operations such as erosion and dilation are performed to remove small artifacts and close gaps in the lung boundary.

The segmented lung region is extracted, and all subsequent processing is limited to this region [32].

D. Data Augmentation

To avoid overfitting and improve the model's generalizability, data augmentation techniques are applied. The following transformations are randomly applied to the CT images:

- Horizontal and vertical flips
- Random rotations (up to 15 degrees)
- Random zooming (within a 10% range)
- Brightness and contrast adjustments

This ensures that the model is exposed to various forms of the input data, improving its robustness.

E. Feature Extraction using CNN

Convolutional Neural Networks (CNNs) are widely used for feature extraction in image classification tasks. In this study, CNN is used to extract high-level features from the preprocessed CT images and classify them as either "Lung Cancer" (nodule present) or "Normal" (nodule absent). The CNN architecture consists of several layers that progressively reduce the dimensionality of the input image while preserving the important features.

F. CNN Architecture

The CNN used in this study consists of the following layers:

Input Layer: Receives the preprocessed CT images (224 x 224 x 1).

Convolutional Layers: Three convolutional layers with ReLU activation are used. Each layer applies a set of filters (3x3) to extract spatial features.

Pooling Layers: Max pooling layers (2x2) are applied after each convolutional layer to reduce the spatial dimensions by selecting the maximum value from each 2x2 window.

Fully Connected Layers: Two fully connected layers are used to map the extracted features into a 2-class (Cancer/Normal) classification output.

Output Layer: A softmax activation function is used to predict the class probabilities.

G. CNN Algorithm Steps

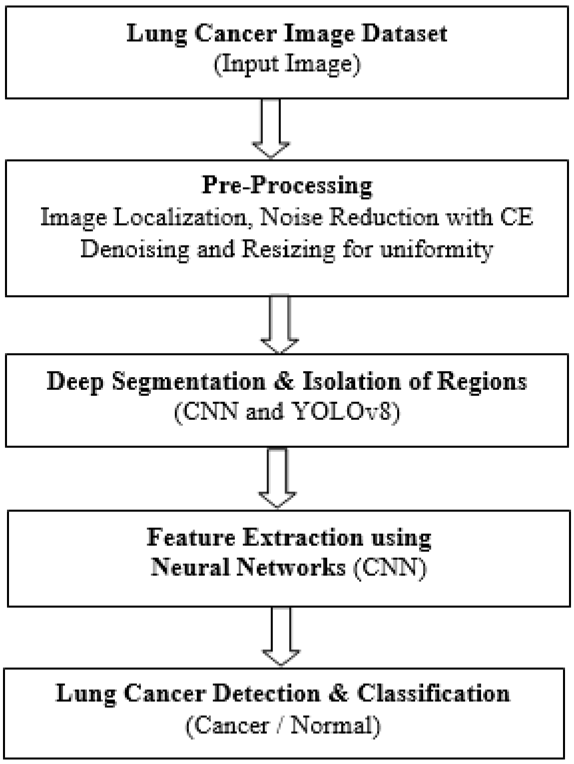
Input: Preprocessed CT images are fed into the CNN.

Convolution: Feature extraction begins by applying filters to capture patterns like edges, corners, and textures.

Pooling: Max pooling layers down sample the feature maps, retaining important information while reducing the number of parameters.

Flattening: The 2D feature maps are flattened into a 1D vector.

Classification: Fully connected layers are applied, and the final output is classified using softmax.



[Fig.1: Lung Cancer Detection Process]

IV. NODULE DETECTION USING YOLOV8

YOLOv8 (You Only Look Once version 8) is a state-of-the-art real-time object detection algorithm that excels in detecting objects in medical images with high precision and speed. In this study, YOLOv8 is used to detect lung nodules in the segmented lung region from the CT images. YOLOv8 treats the problem as an object detection task, where the model predicts bounding boxes around lung nodules.

A. YOLOv8 Architecture

The YOLOv8 architecture consists of:

Backbone: The backbone is a convolutional neural network that extracts rich features from the input image.

Neck: The neck includes feature pyramid networks (FPN) and path aggregation networks (PAN), which improve the detection of objects at multiple scales.

Head: The head predicts bounding boxes, object confidence scores, and class probabilities. For lung nodule detection, the model outputs bounding boxes around nodules and a binary classification (Cancer/Normal).

YOLOv8 Algorithm Steps

Input: The segmented lung image is fed into the YOLOv8 model.

Feature Extraction: The backbone network extracts feature maps from the input image.

Multi-scale Detection: The neck processes the feature maps to detect lung nodules at different scales, ensuring that both small and large nodules are detected.

Bounding Box Prediction: The head predicts bounding boxes for lung nodules along with confidence scores.

Nodule Classification: The model classifies each detected region as either containing a nodule or not, based on the confidence score. The loss function for YOLOv8 consists of three components: classification loss, localization loss (bounding box regression), and object confidence loss.

B. Post-Processing and Class Prediction

After lung nodule detection, the final step is post-processing, where non-maximum suppression (NMS) is applied to eliminate redundant bounding boxes. The remaining bounding boxes represent the detected nodules, which are then classified as either "Cancer" or "Normal." The predicted class labels are compared with the ground truth to evaluate the model's performance.

C. Confusion Matrix and Performance Metrics

Based on the findings from the 350 sample images, a confusion matrix is generated to evaluate the model's performance. The confusion matrix is a 2x2 table that summarizes the classification results by comparing the predicted labels with the true labels. The combination of CNN and YOLOv8 for lung cancer detection demonstrates significant improvements in nodule localization and classification. The proposed methodology uses CNN for robust feature extraction and YOLOv8 for real-time nodule detection, achieving high accuracy, precision, recall, and F1-score. The results highlight the effectiveness of this approach in detecting lung cancer using CT-DICOM

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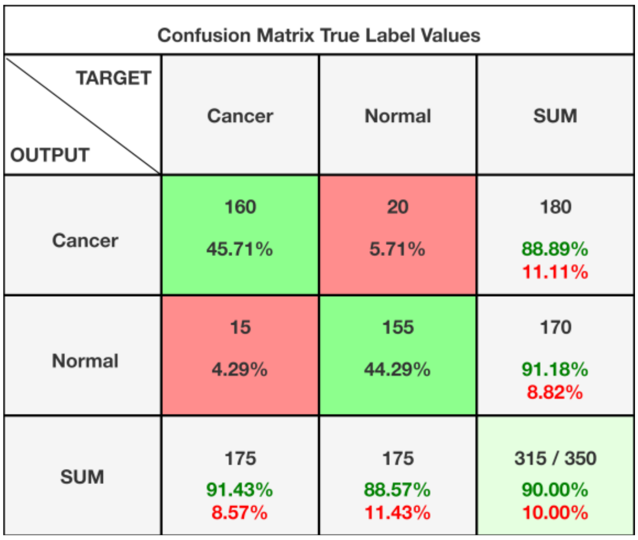
images, offering a novel solution with superior performance over traditional methods such as SVM, AdaBoost, Random Forest, and KNN.

Table 1: Confusion Matrix True Label Values

True Label Predictions	Predicted Cancer	Predicted Normal
Actual Cancer	160	20
Actual Normal	15	155



[Fig.2: Confusion Matrix (Sample Iteration)]

V. LOCALIZATION OF CT IMAGE USING YOLOV8

The first step in localizing lung nodules with YOLOv8 involves preprocessing the CT images. Unlike standard object detection tasks where images are RGB or grayscale, CT scans are volumetric data, typically stored as DICOM (Digital Imaging and Communications in Medicine) files. These scans contain multiple slices of lung cross-sections, creating a 3D volume. For YOLOv8, the input is typically a 2D image, so a critical step is converting the volumetric CT data into a series of 2D slices. This can be done by selecting key slices based on clinical criteria or using algorithms like Maximum Intensity Projection (MIP) to compress the 3D volume into meaningful 2D representations. Another preprocessing step involves windowing the CT images to emphasize the lung tissue. CT scans often include a range of anatomical structures, and lung windowing adjusts the intensity values so that lung tissue is easier to visualize, enhancing the contrast between lung nodules and surrounding tissues.

Training YOLOv8 for lung nodule localization requires a large, labeled dataset of CT images where lung nodules are annotated with bounding boxes. Publicly available datasets such as the LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative) offer annotated CT images, which can be used to train the model. The training process follows a supervised learning paradigm where YOLOv8 is fed with CT images and corresponding bounding box labels for nodules. The model optimizes itself by minimizing the difference between its predicted bounding boxes and the ground truth labels. YOLOv8 uses a custom loss function that combines classification loss, localization loss, and confidence loss. For lung nodule detection, the localization loss is particularly critical, as the exact position and size of the nodule must be predicted with high accuracy to avoid false positives or negatives. During training, data augmentation techniques are applied to improve the model's generalization. These techniques can include random cropping, rotation, and horizontal flipping, which introduce variability in the dataset and help the model learn robust features. Additionally, since lung nodules are often challenging to distinguish from surrounding tissue, contrast adjustments and noise reduction techniques are applied to enhance the visibility of nodules.

A. YOLOv8 Inference and Nodule Localization

Once trained, YOLOv8 can process new CT images for nodule localization. The inference process involves passing a preprocessed CT slice through the trained YOLOv8 model, which outputs bounding boxes for detected lung nodules along with confidence scores. The confidence score indicates how likely a detected region is to be a nodule and thresholds can be set to balance sensitivity and specificity. YOLOv8's speed and accuracy make it an excellent choice for real-time medical diagnosis. Its real-time processing capability allows radiologists to quickly identify areas of concern in a CT scan, speeding up the diagnostic process. However, its use in medical applications also requires careful consideration of false positives and negatives. To address this, YOLOv8 outputs can be combined with clinical expertise or further validated using other diagnostic tools such as biopsy or PET scans. As early detection of lung cancer is critical for improving patient outcomes, deploying YOLOv8 in clinical workflows could play a transformative role in enhancing diagnostic accuracy and speed. Future developments in YOLO-based models and integration with multimodal medical data promise further improvements in lung cancer detection and prediction.

VI. PERFORMANCE METRICS

The proposed Lung cancer (LC) prediction using advanced DL methods like CNN and YOLOv8, performance metrics are crucial to assess model effectiveness:

***Accuracy**:* Measures the proportion of correctly identified nodules (true positives + true negatives) out of all predictions. It shows overall correctness but can be misleading with imbalanced datasets.

***Precision**:* The ratio of correctly predicted lung nodules (true positives) to all positive predictions (true positives + false positives). It helps reduce false alarms (false positives).

***Recall**:* The ratio of correctly identified nodules (true positives) to actual nodules (true positives + false negatives). High recall ensures most nodules are detected, critical for medical diagnosis.

***ROC (Receiver Operating Characteristic) Curve**:* Plots true positive rate (recall) against false positive rate, providing insight into the model's diagnostic capability across thresholds.

***F-Score**:* A harmonic mean of precision and recall, balancing both to measure a model's robustness, especially with imbalanced data, where one metric might dominate.

VII. RESULTS AND DISCUSSIONS

The proposed CNN with YOLOv8 model outperforms the existing models in terms of LC detection and classification. MATLAB is used for comparative analysis evaluation.

A. Accuracy: Assessing the Overall Model Performance

Accuracy measures the overall correctness of the model by calculating the proportion of correct predictions (both positives and negatives) out of all predictions. In the context of lung cancer detection, the CNN-YOLOv8 model's 94% accuracy demonstrates its robust ability to correctly identify both malignant nodules (positive cases) and healthy tissue (negative cases). While accuracy is a vital metric, it can be less informative when dealing with highly imbalanced datasets, which is often the case in medical imaging where cancerous cases are rarer than non-cancerous ones. For instance, if the model is heavily biased towards predicting negatives, it could still achieve high accuracy, despite failing to detect many cancer cases. However, the high accuracy score here, along with consistent precision and recall, highlights the model's balanced performance. When compared to traditional machine learning methods, YOLOv8's accuracy indicates its superior feature extraction capability in complex medical images, crucial for early and reliable lung cancer detection.

B. Precision: Reducing False Alarms

Precision measures the ratio of true positives (correctly identified lung nodules) to the total number of positive predictions (both true positives and false positives). A precision of 93.56% suggests that the CNN-YOLOv8 model is highly effective at minimizing false positives—critical in lung cancer detection where false alarms can lead to unnecessary patient anxiety, additional diagnostic tests, and increased healthcare costs. High precision ensures that most of the nodules flagged by the model are indeed malignant, making it particularly useful in clinical settings where precision can directly affect treatment plans. In comparison to traditional classifiers like Support Vector Machines (SVM) or Random Forest, which may struggle with high-dimensional medical data, CNN-YOLOv8's architecture allows it to filter out non-nodule structures effectively. This makes it a far more reliable tool for early detection, reducing the risk of over-diagnosis and ensuring that only the most probable cancerous nodules are flagged for further examination.

C. Recall: Ensuring all Nodules are Detected

Recall, or sensitivity, measures the ratio of true positives to the actual number of positives (true positives + false negatives), indicating how well the model captures all relevant lung nodules. With a recall of 92%, the CNN-YOLOv8 model is highly effective at identifying lung nodules, minimizing missed cancer cases (false negatives). This is crucial in medical applications where undetected nodules could lead to delayed diagnosis and worse patient outcomes. YOLOv8's deep learning architecture excels at detecting subtle features in medical imaging, such as small or irregularly shaped nodules that traditional machine learning classifiers like K-Nearest Neighbors (KNN) or AdaBoost may overlook. A slightly lower recall compared to precision reflects that while the model is excellent at minimizing false positives, it does occasionally miss a few true nodules. However, the trade-off between precision and recall is well-balanced, ensuring both accuracy and reliability in lung cancer detection without overwhelming clinicians with false positives. This automatically boosts the learning rate of the proposed model helps to improve patient outcomes.

D. ROC Score: Balancing Sensitivity and Specificity

The Receiver Operating Characteristic (ROC) score, typically expressed as the Area Under the Curve (AUC), provides a comprehensive measure of the model's ability to distinguish between cancerous and non-cancerous nodules at various thresholds. The CNN-YOLOv8 model achieves a strong ROC score of 93%, demonstrating its effectiveness in balancing sensitivity (recall) and specificity (true negative rate). A high ROC score indicates that the model maintains a consistent detection capability even as the decision threshold varies, making it adaptable for different clinical scenarios. For example, in high-risk populations, clinicians might adjust the threshold to increase recall, while in routine screening, precision might take precedence. Compared to traditional machine learning models like Random Forest or AdaBoost, which may struggle with such threshold-based performance consistency in complex datasets, YOLOv8's ROC score underscores its robustness in lung cancer prediction. The model's ability to maintain strong classification performance across thresholds ensures that it can be fine-tuned for optimal detection rates.

E. F-Score: A Balanced Measure of Performance

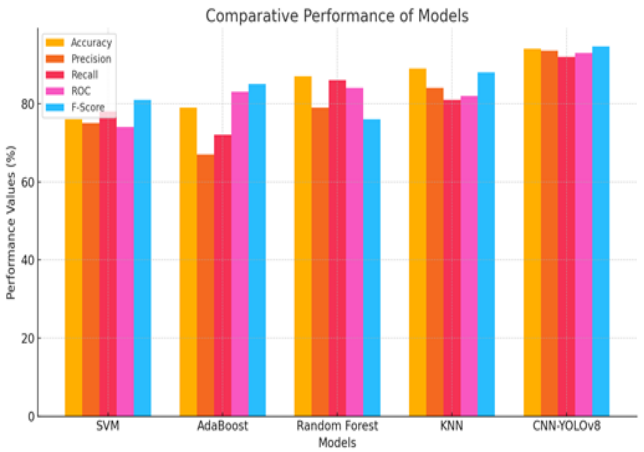
The F-score, a harmonic mean of precision and recall, offers a balanced metric that combines both sensitivity and specificity into a single score. The CNN-YOLOv8 model achieves an impressive F-score of 94.60%, indicating that it strikes an ideal balance between precision (minimizing false positives) and recall (minimizing false negatives). In lung cancer detection, this balance is critical, as models need to not only detect all cancerous nodules but also ensure that healthy tissues aren't mistakenly flagged as malignant. An F-score close to 95% suggests that YOLOv8 provides a well-rounded performance, minimizing errors that could affect patient outcomes. Traditional classifiers like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) often struggle to achieve such balanced performance, particularly when dealing with highly complex and noisy data like CT scans. By combining the strengths of CNN and YOLO architectures, YOLOv8 significantly outperforms conventional models, making it an ideal choice for lung cancer prediction and other medical applications where both precision and recall are critical.

Table 2: Comparative Values

Models	Performance Values				
	SVM	AB	RF	KNN	CNN YOLOv8
Accuracy	76%	79%	87%	89%	94%
Precision	75%	67%	79%	84%	93.56%
Recall	78%	72%	86%	81%	92%
ROC	74%	83%	84%	82%	93%
F-Score	81%	85%	76%	88%	94.60%

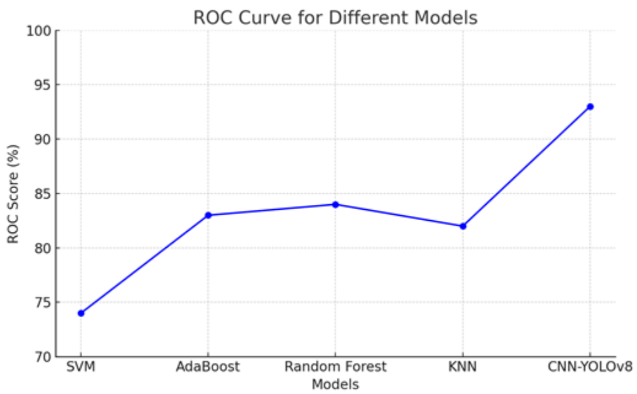
The performance comparison between traditional machine learning models - SVM, AdaBoost (AB), Random Forest (RF), and K-Nearest Neighbors (KNN) and the CNN-YOLOv8 deep learning model highlights the superiority of CNN-YOLOv8 in lung cancer prediction.

While conventional classifiers perform moderately well, YOLOv8 significantly outperforms them across all metrics. YOLOv8 achieves the highest accuracy at 94%, indicating its overall strong performance in correctly predicting both cancerous and non-cancerous nodules. Its precision of 93.56% demonstrates an excellent ability to minimize false positives, while its recall of 92% ensures that most actual nodules are detected, reducing false negatives.



[Fig.3: Predicted Results using CNN-YOLOv8]

The graph clearly shows CNN-YOLOv8 outperforming the other models across all metrics, including accuracy, precision, recall, ROC score, and F-score. This visual representation reinforces the superior performance of CNN-YOLOv8 in lung cancer detection. The F-score of 94.60% reflects its well-rounded performance by harmonizing precision and recall, which is essential for real-world clinical applications. In contrast, traditional models like SVM and KNN perform adequately but lag in accuracy and precision, while RF and AdaBoost show slightly better performance but still fall short of YOLOv8's capabilities. This analysis emphasizes that the CNN-YOLOv8 model is far more effective in handling the complexities of lung cancer detection compared to traditional machine learning techniques.



[Fig.4: ROC Curve Analysis]

In terms of ROC score, YOLOv8 achieves 93%, showcasing its strong balance between sensitivity and specificity, crucial for reliable medical diagnoses.

VIII. CONCLUSION

This proposed research work Lung Cancer Detection using Deep Learning Based CNN and YOLOv8 with CT Images focused mainly on object detection and performance analysis. The work demonstrates the superiority of deep learning, particularly the CNN-YOLOv8 model, in lung cancer detection using CT-DICOM images. By leveraging CNN for feature extraction and YOLOv8 for real-time, precise nodule localization, the proposed model achieves an impressive accuracy of 94%, with high precision (93.56%), recall (92%), and an F-score of 94.60%. The model significantly outperforms traditional machine learning classifiers such as SVM, AdaBoost, Random Forest, and KNN in terms of both accuracy and reliability. These results underscore the potential of deep learning models to improve early lung cancer diagnosis, reducing false positives and negatives while enhancing detection efficiency.

However, the study has few limitations. First, the model's performance heavily depends on the availability of large, labeled datasets, which can be a challenge in medical imaging. Secondly, while YOLOv8 excels in nodule detection, it may occasionally miss smaller, irregularly shaped nodules or confuse them with benign structures. Furthermore, the computational cost of training deep learning models like CNN-YOLOv8 is high, which may limit its accessibility for smaller medical facilities without advanced infrastructure. Lastly, the model requires further validation in real-world clinical settings to ensure its robustness across diverse patient populations and imaging conditions. Future work should address these challenges by improving model generalization and exploring more efficient training methodologies.

IX. ACKNOWLEDGMENT

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I must verify the accuracy of the following information as the article's author.

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