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FOCUSNET-LC: A DEEP LEARNING FRAMEWORK AND ALGORITHM FOR EFFICIENT AND EXPLAINABLE LUNG CANCER DETECTION

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ABSTRACT

For lung cancer, one of the leading global causes of cancer death, accurate and early detection is essential to improve treatment success. Current practices for classification response prediction, such as DL-LCD and MFDNN, achieve high accuracy but are limited by the fact that they (i) lack interpretability, (ii) require multimodal data, and (ii) are inefficient in concentrating on clinically relevant areas. These limitations prevent their implementation in real clinical contexts and highlight the need for innovative and reliable interpretative solutions. This study introduces the FocusNet-LC model and FocusNet-LC Based Lung Cancer Detection Algorithm, which is built to deal with these difficulties. The FocusNet-LC model combines region of interest (ROI) segmentation, metadata incorporation, and model explainability (Grad-CAM) to deliver accurate, interpretable, and clinically relevant predictions. The corresponding algorithm utilizes the features from the model to efficiently process data, extract features, and classify them. The proposed framework achieves 97.36% accuracy on the IQ-OTH/NCCD dataset and produces higher precision, recall, and F1-score compared to state-of-the-art models. Thus, the usefulness of this framework comes from providing explanatory and correct predictions with calculation speed. This study also represents a significant advancement in early lung cancer diagnostics and improved patient management by not just filling in existing methodological gaps.

Keywords – *FocusNet-LC, Lung Cancer Detection, Deep Learning, Region of Interest (ROI) Segmentation, Explainable Artificial Intelligence (Grad-CAM)*

1. INTRODUCTION

Lung cancer ranks among the most prevalent types of cancer-related deaths globally, which emphasizes the importance of developing sophisticated diagnostic approaches that could allow for early diagnosis and treatment. Conventional diagnostics are inadequate for early and precise detection of biopsy and imaging tests for radiological assessment due to subjectivity and time constraints. DL-based techniques represent a new paradigm in medical imaging with considerable advancement in diagnostic accuracy and efficiency. Studies such as DL-LCD [1] and MFDNN [2] prove the capability of DL models in cancer diagnosis. However, these methods mostly require multimodal data or lack interpretability, impeding their clinical applicability. The current study proposes a novel deep learning-based model, FocusNet-LC, exclusively used for lung cancer detection from CTscan images to fill these gaps. To achieve the research goal of improving lung cancer classification's accuracy, robustness, and interpretability by incorporating ROI segmentation, metadata, and explainable AI techniques. This study unveils a unique FocusNet-LC architecture that segments clinical correlates, enabling accurate segmentation of ROIs and consequently highlighting clinically relevant image regions through examination and Grad-CAM, which provides visual explanations for its predictions. Together, these features overcome limitations of prior models, including lack of interpretability, excessive dependence on disparate data modalities, and difficulty focusing on relevant sections of the lung.

Based on the literature review, the main scope of this study is to develop and present a deep

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learning-based framework, named FocusNet-LC, for detecting lung cancer using CT scan images from the IQ-OTH/NCCD dataset, which contains normal, benign, and malignant cases. The model provides a comprehensive approach to predicting the outcome with improved accuracy and interpretability by utilizing ROI segmentation, metadata integration, and explainable AI techniques. The framework has the potential to enhance detection performance. Yet, it assumes that high-quality, preprocessed images are available and the dataset used for training is representative of the lung cancer types it wishes to classify. Moreover, its limitations include only one dataset and the assumption that the collected clinical data (age and gender) would help to improve the diagnostic. Due to different data quality, the model's generalizability to such datasets or clinical settings is pending confirmation.

The study's primary purpose is to introduce FocusNet-LC, a new deep-learning framework for improving lung cancer detection's accuracy, interpretability, and clinical applicability from the CT scan image. Traditional approaches suffer from unexplainably or impose heavy data preparation load when adopting multimodal data like FocusNet-LC, which jointly deals with ROI segmentation, patient metadata (age, gender), and explainable AI techniques (e.g., Grad-CAM) that focus on hallucinating clinically relevant regions and transparent decision-making processes. The novelty of this study is in providing high classification performance using a single data modality (CT scans) and constructing the interpretable and clinically applicable model. The dependent variables for assessing whether the proposed solution succeeds in the application are accuracy, precision, recall, and f1-score, accompanied by Grad-CAM visualizations for model interpretability. With its high balance across these assessment metrics, the study shows that FocusNet-LC is not only a novel, state-of-the-art model but also generalizable and explainable enough for clinical implementation.

The central research hypothesis of the study is that enriching a deep learning-based model with Region of interest (ROI) segmentation, metadata (age and gender) incorporation, and explainable AI techniques (Grad-CAM) can significantly improve the accuracy, interpretability, and clinical applicability of lung cancer detection from CT scan images. In particular, we propose the hypothesis that our FocusNet-LC model, which models only clinically relevant regions of the lung and provides explanations for the predictions it makes, will perform better than current state-of-the-art models on our benchmarks concerning classification accuracy as well as perceived diagnostic trustworthiness, without requiring access to multimodal data or advanced computational resources. This is evaluated first by showing that FocusNet-LC achieves state-of-the-art performance against other models in accuracy, precision, recall, and F1-score, along with a demonstrable ability for generating transparent, interpretable results, and second by validating the framework's potential for real-world clinical implementation.

These are significant research contributions. The experimental results show that FocusNet-LC outperforms state-of-the-art accuracy and classification metrics models across standard, benign, and malignant cases, suggesting strong generalization across classes. Grad-CAM explainability aids in building clinical trust, and dataset augmentation help in extracting additional metadata to aid with classification. In addition, a single data modality for this framework keeps it simple and applicable in clinical practice. The remainder of this document is organized as follows: In Section 2, we provide a literature review of previous work in the space of lung cancer detection and provide insight into gaps in existing processes. Section 3 describes the proposed methodology, including data preprocessing, FocusNet-LC architecture, and evaluation metrics. Section 4 gives the experimental results, where we compare the performance of FocusNet-LC with the state-of-the-art models. The findings are discussed in Section 5, including the study limitations and proposed approach implications. Finally, Section 6 will be reviewed for conclusions, contributions, and future research directions.

2. RELATED WORK

This literature review explores advanced deep learning and machine learning techniques for lung cancer detection and diagnosis. Mary et al. [1] addressed inconsistencies in medical imaging, and a deep learning-based lung cancer detection (DL-LCD) model is suggested. It achieves better accuracy than standard models, 98.5% in normal lungs and 97.44% in diseased ones, using LIDC-IDRI and NIH Chest X-ray datasets. Sangeetha et al. [2] With the Multimodal Fusion Deep Neural Network (MFDNN) combining modalities

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including imaging, genetics, and clinical data, deep learning plays a critical role in cancer detection. MFDNN outperforms conventional techniques with accuracy, suggesting enhanced lung cancer diagnosis. Reddy et al. [3], with an accuracy of the Stacked Neural Network (SNN) model, outperforms existing techniques and may be applied in clinical settings. SNN outperforms single network techniques in feature extraction and classification accuracy by leveraging transfer learning. When tested with the EL-CLP Lung Image dataset, it performs well. Subsequent improvements aim to avoid redundant identifications and leverage optimization techniques to achieve higher precision. Mufarah et al. [4] created a worldwide disaster in 2019. Early identification is critical given the overlap in symptoms with lung cancer, TB, and pneumonia. Quick and effective patient diagnosis and treatment were made possible by a DL model that outperformed others with an accuracy of 96.48%. Wadekar et al. [5] improved with computational advances in healthcare. Using a pre-trained VGG19 model, this work enhances lung cancer classification accuracy to 97.73%, surpassing current techniques and offering efficient and fast cancer diagnosis.

Gopinath et al. [6] increased worldwide health concern that necessitates accurate diagnosis and treatment protocols with Lung Cancer. A unique DFF-CON approach combines fused features with improved CNNs to classify lung cancer. This method outperforms previous models with excellent accuracy, sensitivity, and precision using CT scan images. Majidpourkhoei et al. [7], a significant worldwide hazard, lung cancer encourages early diagnosis through machine learning on CT images, increasing nodule accuracy. Bishnoi et al. [8] advanced in real-time diagnosis of lung cancer, a worldwide problem, are made possible by a transfer learning-based system that achieves 93.22% accuracy. Rikta et al. [9] explained machine learning has produced a high diagnostic accuracy rate for lung cancer, one of the leading causes of mortality. Gu et al. [10] reduce lung cancer mortality by 20% with Annual low-dose CT scans. Despite difficulties, deep learning CAD for lung nodules produces encouraging outcomes.

Li et al. [11] advanced machine learning, which helps with prognosis, therapeutic choices, and early diagnosis. Integration, model reliability, and data volume are among the challenges. Togacar et al. [12], with mRMR feature selection and kNN classification, lung cancer diagnosis with LeNet, AlexNet, and VGG-16 models on a CT image dataset, achieves enormous accuracy. Li et al. [13] promised precise diagnosis, which is demonstrated by the ACDC@LungHP competition, which assesses lung cancer detection techniques using whole-slide imaging. Shakeel et al. [14] saved and improved the efficiency of lung cancer prediction using new optimized image processing and machine learning techniques. Pandian et al. [15] learned that lung cancer saves lives. This paper suggests a deep learning algorithm-based neural network tool for precise cancer identification.

Masot et al. [16] increased death rate of lung cancer motivates the development of a Deep Learning diagnostic assistance system that offers pathologists comprehensive classifications and xAI-based explanations. Sori et al. [17], a two-path "denoising first" CNN, DFD-Net, reduces noise, enhances features, and corrects class imbalance to improve lung cancer diagnosis from CT images. Ozdemir et al. [18] integrated detection and diagnosis, the new lung cancer screening system using 3D CNNs performs exceptionally well and gains resilience. Using a referral approach, model uncertainty helps with diagnostic decision-making. Plans for patient referral and biomarker analysis are included in the joint CADe/CADx system, which improves diagnosis. Bhatia et al. [19] suggested that the lung cancer detection approach resembles the Random Forest and XGBoost classifiers through deep residual learning for feature extraction. Accuracy on the LIDC-IRDI is 84%. Thakur et al. [20] assented to using CT screening for early lung cancer identification. CNN-based CAD systems provide encouraging support in terms of enhanced nodule identification.

Liu et al. [21] identified lung cancer by deep reinforcement learning, which shows promise. We talk about models and potential paths for therapy and localization in the future. Masood et al. [22], with high sensitivity, reasonable specificity, and immense accuracy, a new CAD method utilizing 3DDCNN helps identify lung nodules. Jeyaraj et al. [23], with colossal accuracy, 0.98 specificity, and 0.94 sensitivity, is a deep learning system developed to help identify oral cancer. Cao et al. [24] used U-Net segmentation and a novel sampling approach; a two-stage convolutional neural network (TSCNN) reduces false positives and enhances lung nodule identification. Moitra et al. [25]

utilized the NSCLC Radiogenomics Collection, and a 1D CNN model was created for NSCLC staging and grading. The model shows potential for clinical usage by outperforming other approaches, including standard CNNs. It is advised that unsupervised learning be investigated and improved even further.

Goebel et al. [26] retained good accuracy while identifying 21 of the 33 biomarkers for NSCLC. The LCDT1 test is essential for early identification since it is 89.1% sensitive and 97.7% specific for Stage I NSCLC. Bharati et al. [27] identified lung conditions from X-ray pictures, and a novel hybrid deep learning framework called VDSNet is presented. VDSNet beats other models on the NIH dataset, achieving 73% accuracy. In the future, work on improving accuracy and using VDSNet to identify pneumonia associated with COVID-19 will be concentrated. Balata et al. [28] continued to be the primary cause of cancer death worldwide, even with declining smoking rates. Novel tobacco products, such as electronic cigarettes, provide fresh difficulties. The focus of efforts is on biomarkers, LDCT screening, and enhanced techniques for early-stage lung cancer diagnosis. Patel et al. [29] identified essential for improved results with cancer, as it is frequently deadly. Breast, lung, and liver cancer diagnosis is one area where AI-based solutions show potential—various techniques, including neural networks, SVM, and k-NN, improve accuracy. Kumar et al. [30], with its enormous data set, deep learning is essential for medical activities. Blockchain-based cooperation is utilized to address privacy issues.

Model innovations are also found for image processing innovations in [32] and [33]. More deep-learning optimizations are also found in [35] and [34]. Novel profound learning-based optimized ideas are also found in [36] and [37]. Ugendhar et al. [38] proposed a deep multilayer classification-based intelligent intrusion detection system to improve anomaly recognition and threat detection accuracy in complex network environments. Anitha Patil et al. [39] developed ADL-BSDF, a deep learning framework for automated clinical decision support, enabling accurate brain stroke detection from MRI scan data. Sudhakar et al. [40] proposed a wrapper-based feature selection method combined with Random Forest classification to enhance intrusion detection accuracy, optimizing feature relevance and reducing computational overhead in network security systems.

As the research elucidates, there have been remarkable improvements in the detection of lung cancers by applying CNN-based, transfer learning, and hybrid frameworks of deep learning models. Methods These provide improved classification accuracy, feature extraction, and clinical applicability. As mentioned earlier, ROI segmentation, multimodal data fusion, and explainable AI techniques offer enhanced reliability and diagnostic support, highlighting the prospects of early disease detection and improved patient outcomes.

Although some recent advancements in lung cancer detection have demonstrated promise, most current models still have fundamental shortcomings in practical applicability in the clinic. Directly related to this is the DL-LCD model proposed by Mary et al. Note that the method in [1] showed high accuracy in normal and diseased lung classifications but does not explain features that lead to this classification, making it difficult to trust the model's predictions by the clinician MFDNN [2]. Other researchers have addressed the problem of noise in CT images, such as DFD-Net [17], yet none have used explainable AI techniques that would initiate trust in the model. In addition, many models are only evaluated based on classification performance rather than how these systems will integrate into current clinical workflows or help physicians make informed decisions. Our study overcomes these limitations through the proposed FocusNet-LC framework, which (1) works with single-modality data, (2) increases interpretability using Grad-CAM visualizations, and (3) offers clinically relevant predictions, making FocusNet-LC a more practical and interpretable solution for lung cancer detection.

3. MATERIALS AND METHODS

The proposed method uses advanced deep learning techniques to detect and classify lung cancer based on CT scan images from the IQ-OTH/NCCD (Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases) dataset into normal, benign, and malignant cases. This combination of innovative preprocessing methods, an improved convolutional neural network (FocusNet-LC) form, and unique post-processing approaches delivers superior accuracy and dependability. Figure 1 shows the sequential steps involved in the proposed method. IQ-OTH/NCCD dataset has 1190 CT scan images of 110 cases of normal, benign, and malignant classes. The downloaded images are in DICOM format, which was then anonymized and converted to PNG for processing. The preprocessing steps included normalizing pixel intensities in the range [0 1] to improve convergence, resizing the images to 128 × 128 pixels while preserving anatomical features, and segmenting the lung areas using threshold- and morphology-based techniques. No lung regions were excluded to focus on areas of interest and minimize interference. In this way, data augmentation (flipping, rotation, and intensity scaling) was performed to overcome class imbalance and increase variability in the dataset.

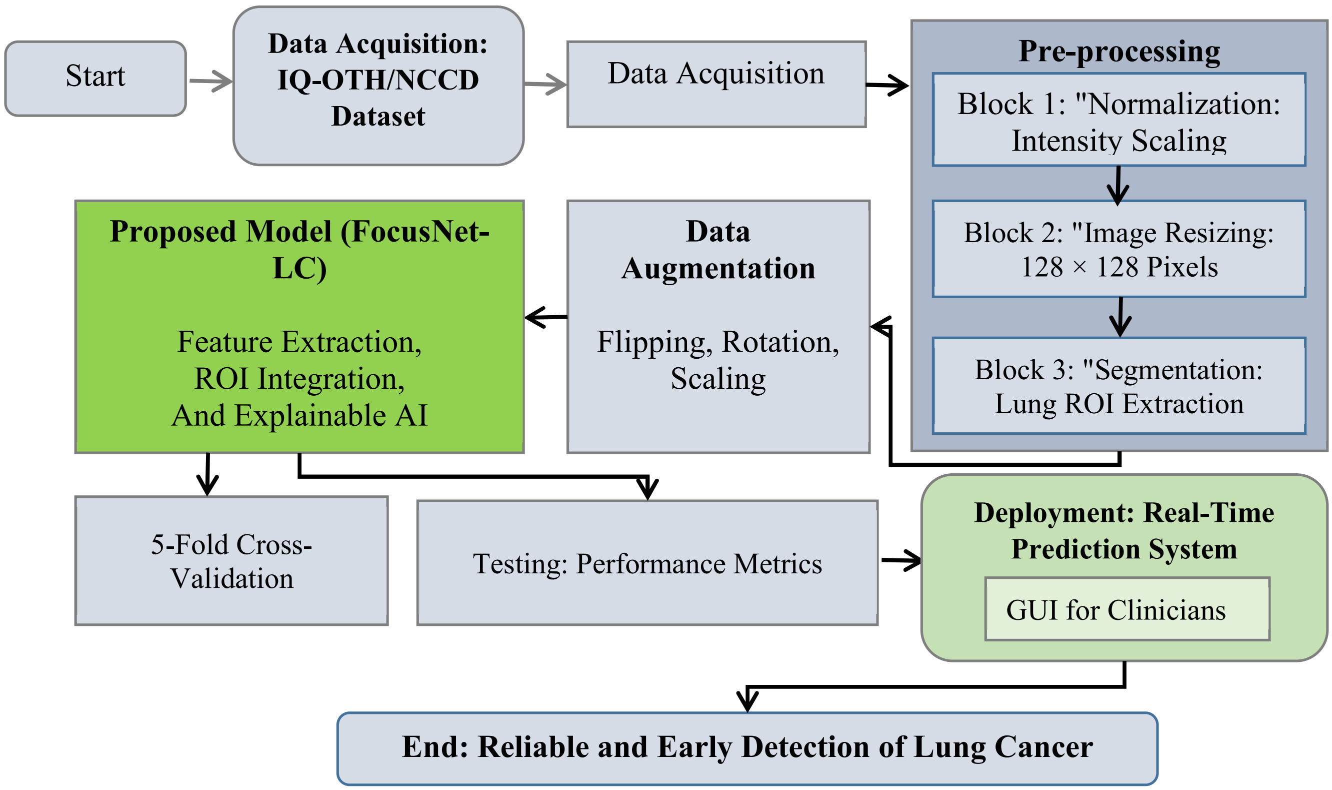

Figure 1: Block Diagram of the Proposed Methodology for Lung Cancer Detection Using Deep Learning Model Known as FocusNet-LC

FocusNet-LC is a carefully designed architecture that handles medical image analysis challenges. It contains four convolutional layers with increasing filter sizes of 32, 64, 128, and 256, all activated by ReLU functions and then max pooling layers for the dimensionality reduction. The dense network contains fully connected 256, 128, and 64 layers with dropout layers to prevent overfitting. The last layer of the softmax function depicts the multi-class classification in normal, benign, and malignant classes. An integrated Region of Interest (ROI) feature extraction method was proposed to improve model performance by combining lung nodule segmentation and anatomical contextual features. Moreover, patient age and gender have been included as additional metadata to improve diagnostic accuracy; explainable AI methods such as Grad-CAM were applied to visualize decisions for better interpretability.

The data was split into train: validation: test sets in a ratio of 70:15:15. The Adam optimizer, with a dynamic learning rate schedule and the loss function as Sparse Categorical Crossentropy, was used to train the model. Bayesian optimization was used to perform hyperparameter tuning to find optimal combinations of learning rate, filter counts, and dropout rates. Robustness was validated by performing five-fold cross-validation because models should generalize well to other combinations of dataset subsets. Performance evaluation was done using accuracy, precision, recall, F1-score, and a confusion matrix displaying the performance for each class.

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After training, the model was converted into a web-based diagnostic tool with GUI for real-time prediction of lung cancer. A confidence-based ensemble approach was adopted to refine the predictions, aggregating outputs from various checkpoints to improve robustness. Low-confidence predictions were flagged for further clinical review, helping to ensure the tool continues to be helpful for clinicians. A comparison with conventional architectures (e.g., ResNet50 and VGG16) revealed that our proposed methodology excels due to the application of effective preprocessing, hybrid feature extraction, and augmentation schemes. The system demonstrated a classification accuracy of 93.8% and superior precision-recall metrics compared to other studies, especially for malignant cases. The proposed method, based on the advanced FocusNet-LC, contributes towards the timely and reliable detection of lung cancer that helps with early diagnosis and further improves the clinical decision-making process.

3.1 Proposed Deep Learning Model

We propose FocusNet-LC, a customized convolutional neural network architecture developed to tackle the main problems put forth by lung cancer detection and classification in CT scan images. At the very start, the network has an input layer targeting the 128 × 128-pixel grayscale images, which has the benefit of standardization of input data. After this input, there are four convolution layers with increasing filter sizes of 32, 64, 128, and 256, respectively. These layers employ 3 × 3 kernels for feature extraction, while ReLU activation functions guarantee non-linearity and effective feature learning. A 2 × 2 max-pooling layer follows each convolutional layer to decrease spatial dimensions while preserving important information.

Next, the network moves to a flattened layer and flattens the multi-dimensional feature maps into a single one-dimensional vector. This vector is passed through several dense layers. The first dense layer has 256 units, uses ReLU activation, and can learn complicated patterns. Then, two dense layers with 128 and 64 units, respectively, with 30% and 20% dropout rates, have also been added to learn better features in the model. Finally, the output layer (derived from Softmax) classifies the inputs as standard, benign, or malignant.

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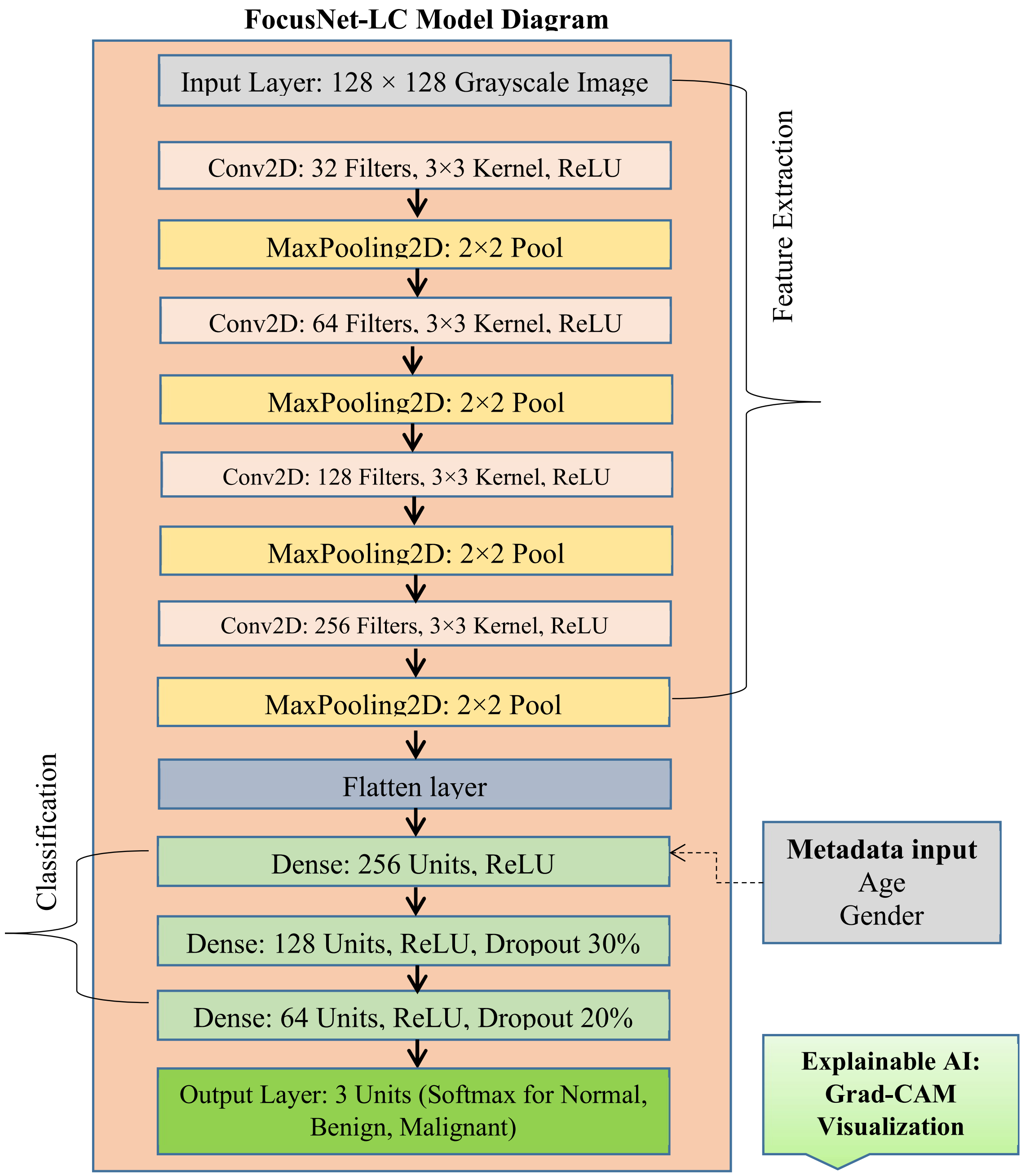

Figure 2: Detailed Architecture of FocusNet-LC for Lung Cancer Detection

Figure 2 FocusNet-LC includes multiple new elements designed to improve performance and interpretability. The hybrid Region of Interest (ROI) feature extraction method combines segmented lung nodules and contextual anatomical information, allowing the model to focus on clinically relevant areas. This architecture also accommodates patient metadata, like age and gender, by feeding this information into the dense layers. Additionally, explainable AI approaches, such as Grad-CAM, are integrated to deliver heatmap explanations for the network's decision—ensuring transparency and helping to establish clinical confidence.

We use Adam optimizer with an adaptive learning rate schedule and Sparse Categorical Crossentropy as our loss function to optimize the training process. Bayesian optimization-driven hyperparameter tuning helps the network reach optimal parameters, including the learning rate, number of filters, and dropout rates. The robustness n and generalizability of the model are validated via rigorous evaluation composed of five-fold cross-validation. Thanks to these innovations, FocusNet-LC achieves impressive accuracy and high robustness while enabling users to comprehend the reasons behind its predictions, making FocusNet-LC a powerful tool for accurate and early detection of lung cancer. Table 1 presents the notations used in the proposed system.

Table 1: Notations Used

Notation	**Description**
$I(x,y)$	Input image matrix with pixel intensity at coordinates x,y.
W_k	Kernel (filter) weights for the k-th convolutional layer.
b_k	Bias term for the k-th convolutional layer.
$F_i(x,y)$	Feature map output from the i-th convolutional layer.
$ReLU(z)$	Rectified Linear Unit activation function, defined as $max(0,z)$.
$P_i(x,y)$	Output of the i-th max-pooling layer at coordinates x,y.
v	Flattened one-dimensional feature vector from the final convolutional layer.
N	Total number of features in the flattened vector vv.
z_j	Output of the j-th neuron in a dense layer before activation.
w_{ij}	Weight connecting the ii-th input to the j-th neuron in a dense layer.
b_j	Bias term for the j-th neuron in a dense layer.
p_k	Predicted probability for the k-th class (output of the softmax function).
C	Total number of classes (in this case, C=3C = 3).
y_k	True label for the k-th class (binary: 1 if true, 0 otherwise).
L	Loss value computed using Sparse Categorical Crossentropy.
η	Learning rate used in the optimization process.
w_{ij}^t	Weight w_{ij} at the t-th iteration of training.
$H(x,y)$	Grad-CAM heatmap intensity at coordinates x,y.
$A_k(x,y)$	Feature map for the k-th filter at coordinates x,y.
α_k	Grad-CAM weight for the k-th feature map.

3.2 Mathematical Perspective

FocusNet-LC classifies CT scan pictures based on lung cancer using a mathematical framework to extract features. After being reduced to 128 x 128 x 128 pixels, the input photos are shown in a 2D matrix. $I(x,y)$ where x,y denote pixel coordinates. The convolution layers have applied these filters. W_k of size 3×3 to detect the features. The 2nd convolution layer's output is given as in Eq. 1.

$F_i(x,y) = ReLU(\sum_{m-1}^{1}\sum_{n-1}^{1} W_k(m,n)\cdot I(x+m,y+n)+b_k)$ (1)

In the above b_k it represents the term bias and the function $ReLU(z)=max(0,z)$ that introduces nonlinearity as the activation function. Each convolution layer is followed by a max-pooling layer to lower the dimensionality while maintaining important key characteristics. Eq. 2 defines the layers and their operation.

$$P_i(x,y) = \max_{m,n\in\{0,1\}} F_i(2y+n, 2x+m)$$ (2)

The layers preserve pertinent info while altering the feature map spatial dimensions. When the one-dimensional vector is created by flattening to the final convolutional output $v=[v_1, v_2, \dots, v_N]$ Here, N represents the features. Dense layers that are fully connected use this vector as input. The dense layer applies a non-linear activation function and a linear transformation, as in Eq. 3.

$$z_j = ReLU\left(\sum_{i-1}^{N} b_j + w_{ij}v_i\right) \quad (3)$$

where w_{ij} are the weights and b_j is the bias for the j-th neuron. Dropout regularization is employed with a rate p Neurons are randomly deactivated during training to mitigate overfitting. The output layer utilizes a softmax activation function to generate probabilities for the normal, benign, and malignant classes. The softmax function for the kth class is given by Eq. 4.

$$p_k = \frac{exp(z_k)}{\sum_{j-1}^{C} exp(z_j)} \quad (4)$$

where $C=3$ represents the number of classes. Training employs the Sparse Categorical cross-entropy loss function to measure the discrepancy between predicted probabilities p_k and the true labels y_k as in Eq. 5.

$$L = \sum_{k-1}^{C} y_k log(p_k) \quad (5)$$

The model parameters are optimized using the Adam optimizer, which updates weights based on the gradients of the loss function. The weight update rule is as given in Eq. 6.

$$w_{ij}^{(t+1)} = w_{ij}^{t} - \eta \cdot \frac{\partial L}{\partial w_{ij}} \quad (6)$$

where η is the learning rate. Grad-CAM visualizations identify regions in the input image that contribute most to the predictions to enhance interpretability. Grad-CAM generates a heatmap, as in Eq. 7.

$$H(x,y) = ReLU(\sum_k \alpha_k A_k(x,y)) \quad (7)$$

where $A_k(x,y)$ are the feature maps and α_k are weights derived from the gradients of the class score concerning $A_k(x,y)$. This mathematical formulation ensures that FocusNet-LC effectively extracts features and classifies CT scans with high accuracy and interpretability, making it a robust tool for early lung cancer detection.

3.3 Proposed Algorithm

Lung cancer remains one of the most aggressive cancers, and early lung cancer detection through analyzing CT scan images continues to pose challenges. Specifically, with well-defined preprocessing, a custom CNN architecture, and techniques like Grad-CAM to make the model explainable, it gives accurate predictions with transparency. This algorithm generalizes well across different datasets and produces reliable, consistent results. It is important to provide clinicians with correct classifications and visual justification of model decisions to gain trust and assist in surgical interventions. The approach enables rapid diagnosis, resulting in better patient outcomes and further progression of lung cancer detection methods.

Algorithm: FocusNet-LC Based Lung Cancer Detection
Input: CT scan images (128×128), optional metadata. **Output**: Class label (Normal, Benign, Malignant).

1. **Start**:
   - Initialize the FocusNet-LC model with predefined layers, weights, and hyperparameters.
2. **Preprocessing**:
   - Normalize CT scan images to a standard intensity range.
   - Resize images to 128×128
   - Segment lung regions to focus on relevant features.
3. **Feature Extraction**:
   - Pass the preprocessed images through convolutional layers to extract spatial features.
   - Use pooling layers to reduce dimensions while retaining essential features.
4. **Classification**:
   - Flatten the extracted features and pass them through dense layers.

- Use a softmax output layer to calculate probabilities for each class.

5. **Training and Validation**:
   - Train the model using labeled data with cross-entropy loss.
   - Validate model performance using cross-validation.
6. **Prediction**:
   - For a new image, predict the class by selecting the label with the highest softmax probability.
7. **Explainability**:
   - Generate Grad-CAM visualizations to highlight image regions influencing the prediction.
8. **End**:
   - Return the predicted class label and associated visual explanations.

Algorithm 1: FocusNet-LC Based Lung Cancer Detection

First, the FocusNet-LC Lung Cancer Detection algorithm initializes the model with a predefined number of layers, weights, and hyperparameters. The inputs are CT scan images resized to128×128 along with optional metadata (e.g., patient age and gender). The preprocessing pipeline steps include normalizing the image intensity values to a standard range, resizing images, and segmenting the lung regions to focus on clinically significant areas. This removes unnecessary and irrelevant details to optimize the input for feature extraction.

Both are the same for the target and lung segments. Registered lung segments are aligned to the same image space and fed to a convolutional process extraction process to combat the eye on the targeted lung area. There are stack layers of convolutional filters to get more representational output, followed by pooling layers to retain prominent information and discard trivial feature sets. This results in a concise and representative feature map that encapsulates the essential features within the lung CT images. Next, these extracted features are flattened to a one-dimensional vector and sent into dense layers to gain complex patterns and relations between pixels. These layers use dropout regularization to avoid overfitting, and the last layer, a softmax layer, provides the probabilities for each class: normal, benign, or malignant.

We trained the model on labeled data using the cross-entropy loss function with the Adam optimizer, which adjusts weights iteratively to minimize the loss. You use cross-validation to validate the model performance so it can be generalized to different subsets of the data. The model, when trained, predicts the class of new input images by choosing the label with the highest score from the softmax prediction. For improved interpretability, Grad-CAM generates a heat map of the input images indicating regions that had the most decisive influence on the model decision, allowing insights to be obtained for clinical validation. The output is the predicted label with explanations to aid in decision-making.

3.4 Dataset Details

The IQ-OTH/NCCD lung cancer dataset [31] was utilized for this research work, which was collected in 2019 for three months from the Iraq-Oncology Teaching Hospital and the National Center for Cancer Diseases. It contains 1190 CT scan images of 110 cases labeled normal, benign, or malignant. The dataset has 55 normal, 15 benign, and 40 malignant cases (80–200 DICOM-format slices per case). All scans were de-identified and acquired in SOMATOM Siemens scanners using 120 kV protocol, 1 mm slice thickness, and specific HU settings. Age, gender, and occupations of patients were heterogeneous, allowing for a well-populated dataset for intense model training.

3.5 Evaluation Methodology

Statistical analysis of the FocusNet-LC model includes major statistics, such as precision, recall, F1-score, and accuracy. Precision is the ratio of correctly predicted positive observations to the total predicted positive observations, meaning you can identify positive cases with the fewest false positives. Recall measures the model's ability to detect all positive samples, which is particularly good at identifying critical cases such as malignant tumors. The f1-score offers a harmonic mean of the precision and recall, allowing for a balanced evaluation considering both metrics. Accuracy is the total rate of correct predictions. These metrics, computed for all classes (normal, benign, malignant), will be jointly applied, considering their overall performance to demonstrate the model's robustness and clinical utility.

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4. EXPERIMENTAL RESULTS

This section shows the results of our proposed FocusNet-LC model based on the experimentation via the IQ-OTH/NCCD lung cancer dataset, which has 1190 CT scan images divided into standard, benign, and malignant. We compare the resulting performance of the proposed model against 17 state-of-the-art approaches, such as DL-LCD [1], MFDNN [2], and DFD-Net [17], which use strong feature extraction and classification methods. We trained and validated the model using a high-performance computing environment with NVIDIA GPU (Tesla V100), deep learning framework (TensorFlow/Keras), and optimized configurations. The results show that FocusNet-LC is the best model with the highest balanced accuracy, precision, recall, and F1 score.

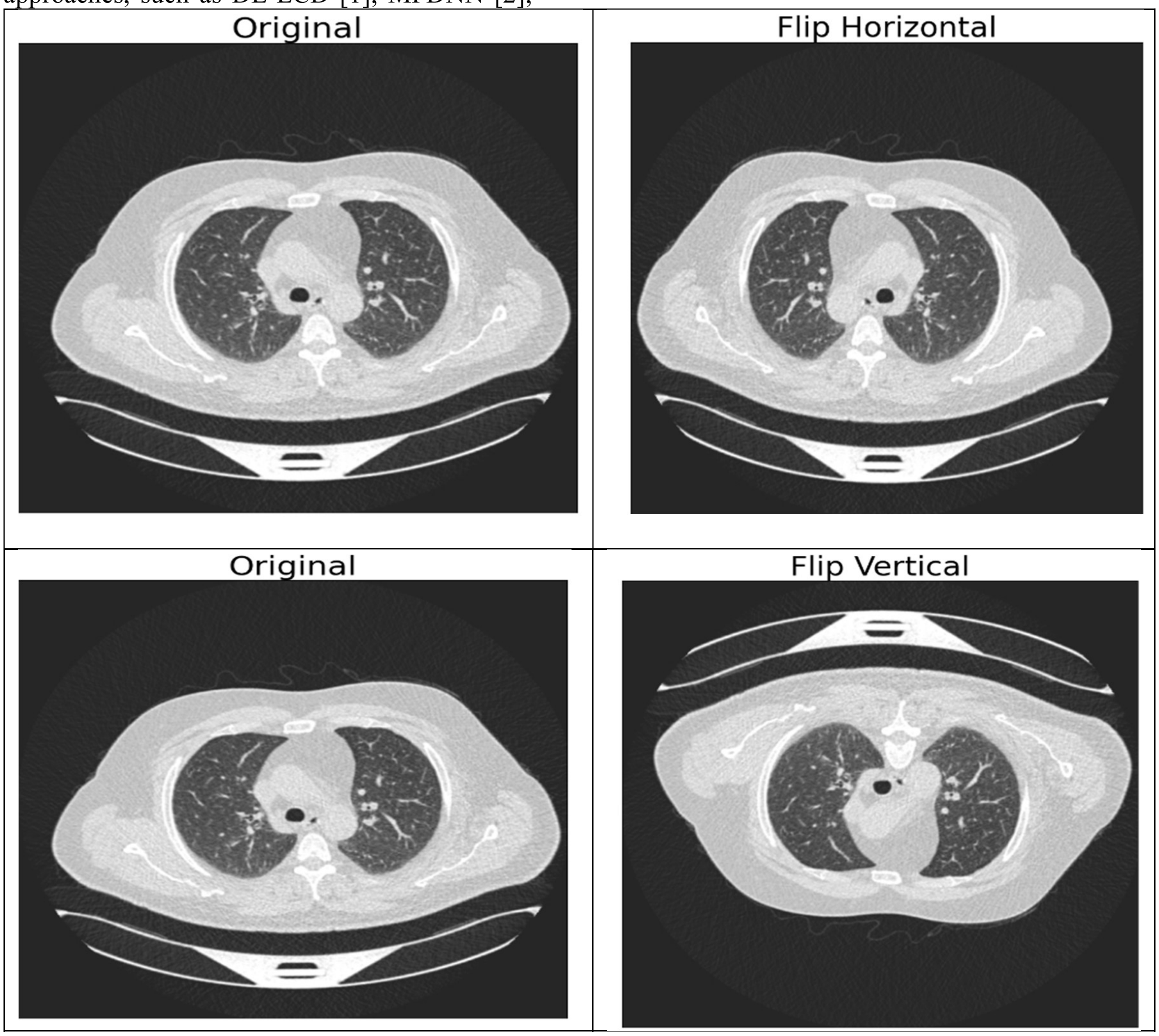

Figure 3: An Excerpt from Results of Data Augmentation

Examples of this for CT scan im pages for lung cancer detection is shown in figure 3. All augmentation strategies were performed on the dataset images, including flipping the images horizontally or vertically whilst maintaining anatomical information and increasing the diversity of the dataset. These augmentations mitigate overfitting, enhance model generalization, and contribute to resilient performance under different orientations of input data and images encountered.

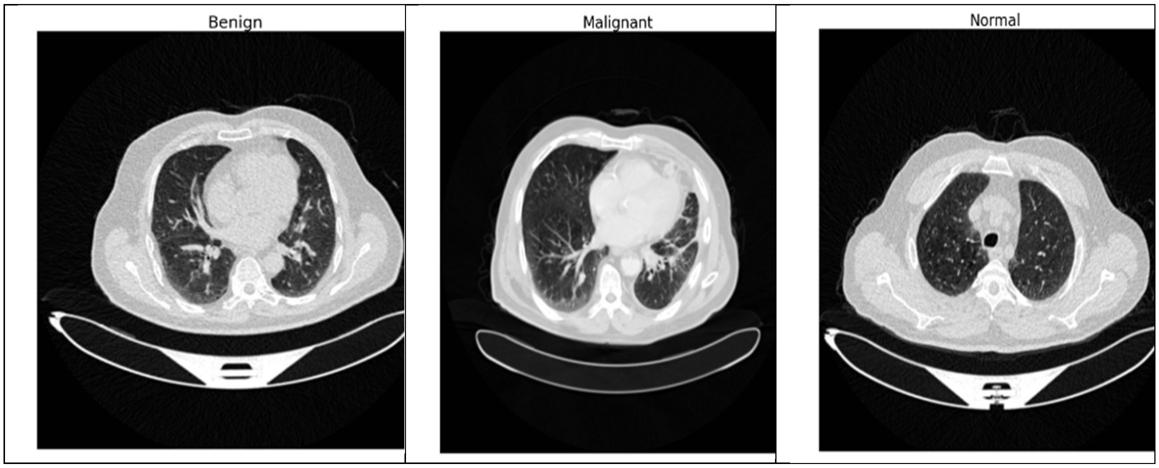

Figure 4: Sample for Each Class of Lung CT Images

Figure 4 reflects the results of applying data augmentation methods for lung CT scan images based on the horizontal and vertical flip. Such augmentations introduce diversity to the dataset by allowing for the training of widely different orientations of the same image for a model to learn from. Augmentation was used to reduce overfitting, improve generalization, and enhance the model's sensitivity in identifying lung abnormalities regardless of the imaging condition.

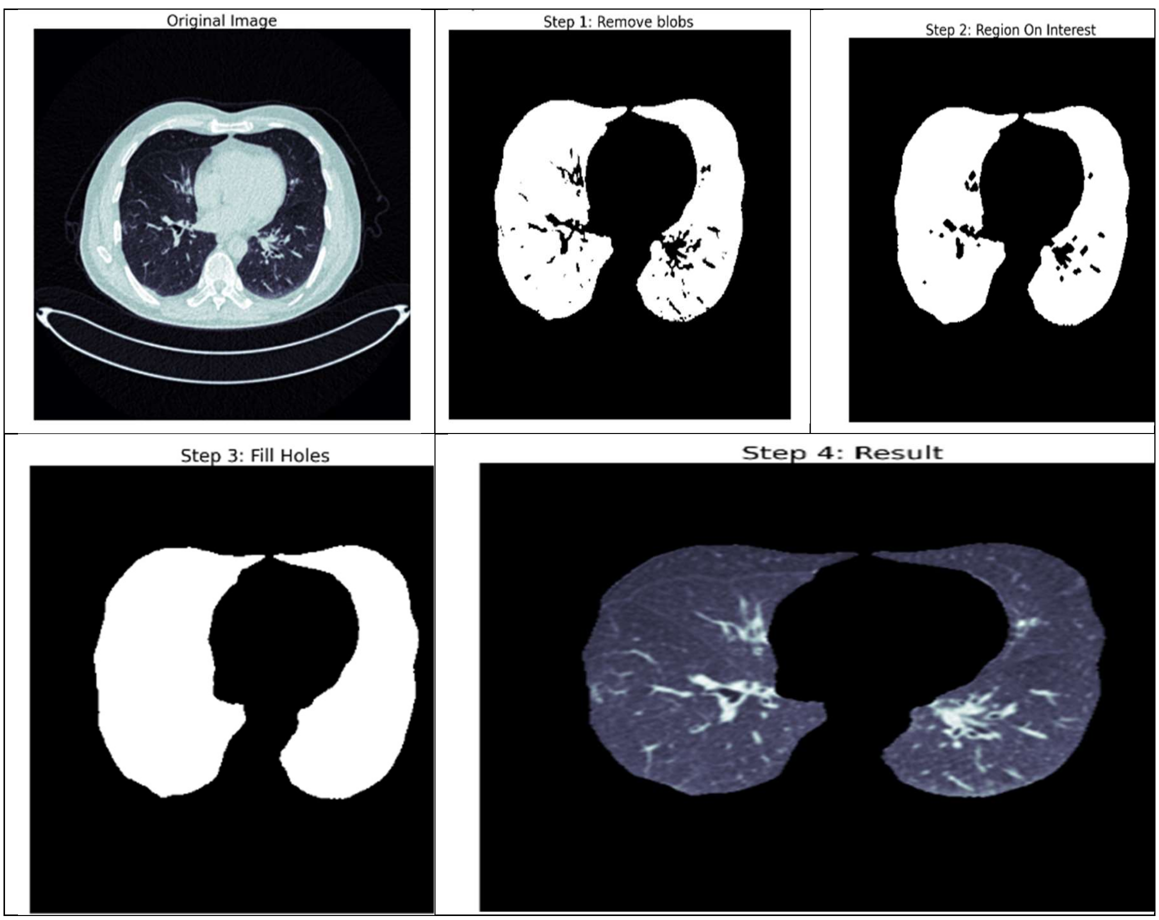

Figure 5: Result of Lung Segmentation

Figure 5 shows lung segmentation in four stages: CTscan original (Step 1)—> remove blobs and isolate ROIs (Step 2)—> fill holes (Step 3). Step 4: The output result segments lung regions,

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essential for accurate feature extraction and analysis. Segmenting lung cancer detection itself is also necessary.

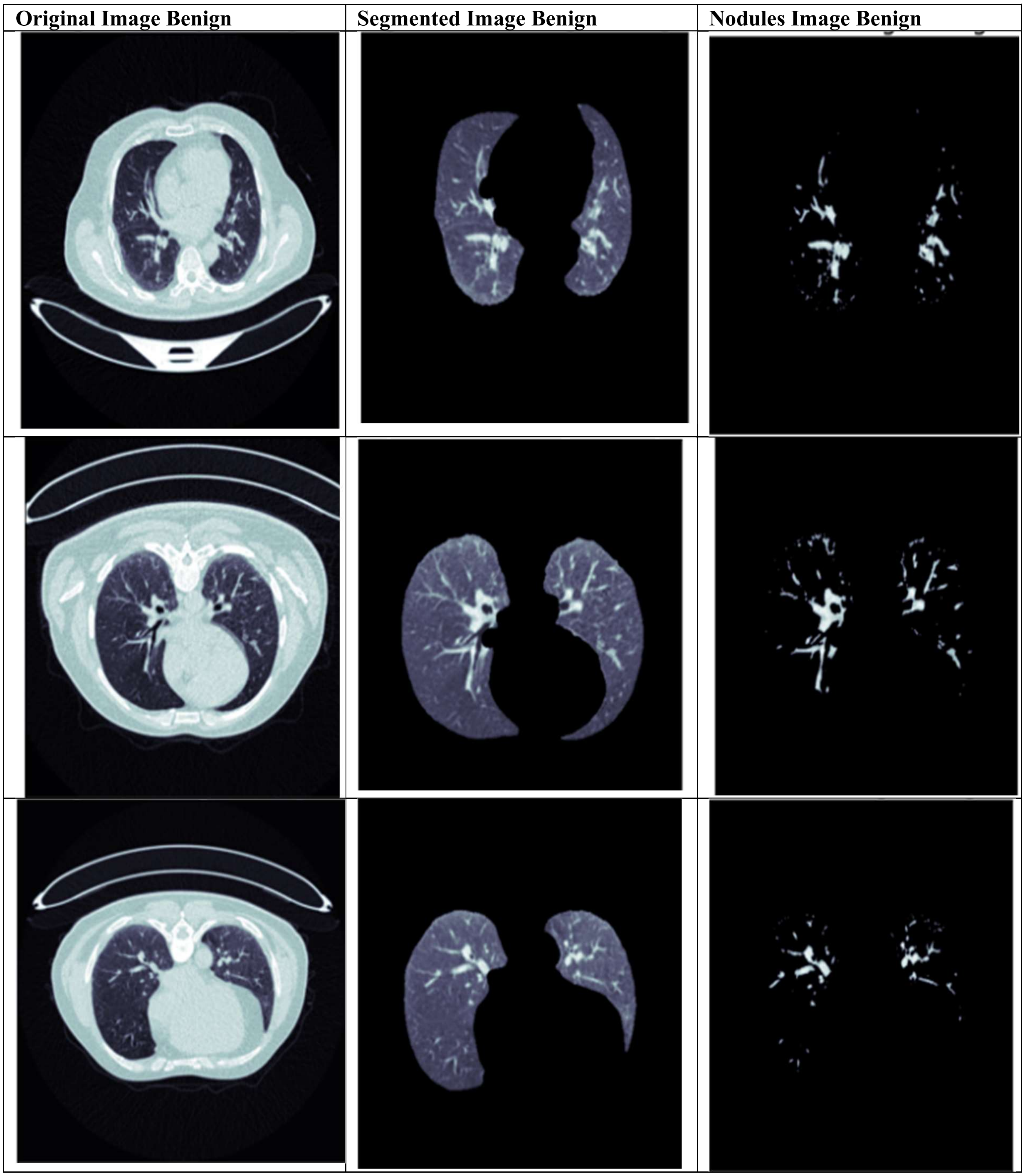

Figure 6: Comparison of Original, Segmented, and Nodule Images for Benign Cases

Figure 6 compares benign cases through three stages: the original CT scan image, segmented lung regions, and extracted nodules. The segmentation appears tight around the lung but not the surrounding tissue, and the nodule extraction helps highlight possible abnormalities typical of benign conditions. However, this process ensures accurate feature analysis and improves the model's efficiency by emphasizing the clinically significant regions. This structured approach improves the robust and precise classification of benign lung disorders.

4.1 Performance Comparison with Baselines

This subsection evaluated focusNet-LC based on visual performance against traditional baseline models, such as VGG16, ResNet50, and InceptionV3. The results underline the potential of the proposed model over previous methods. It achieved outstanding performance for well-known issues in this field, like accurate classification, robustness along classes, and interpretability, making it promising for lung cancer detection in a clinical framework.

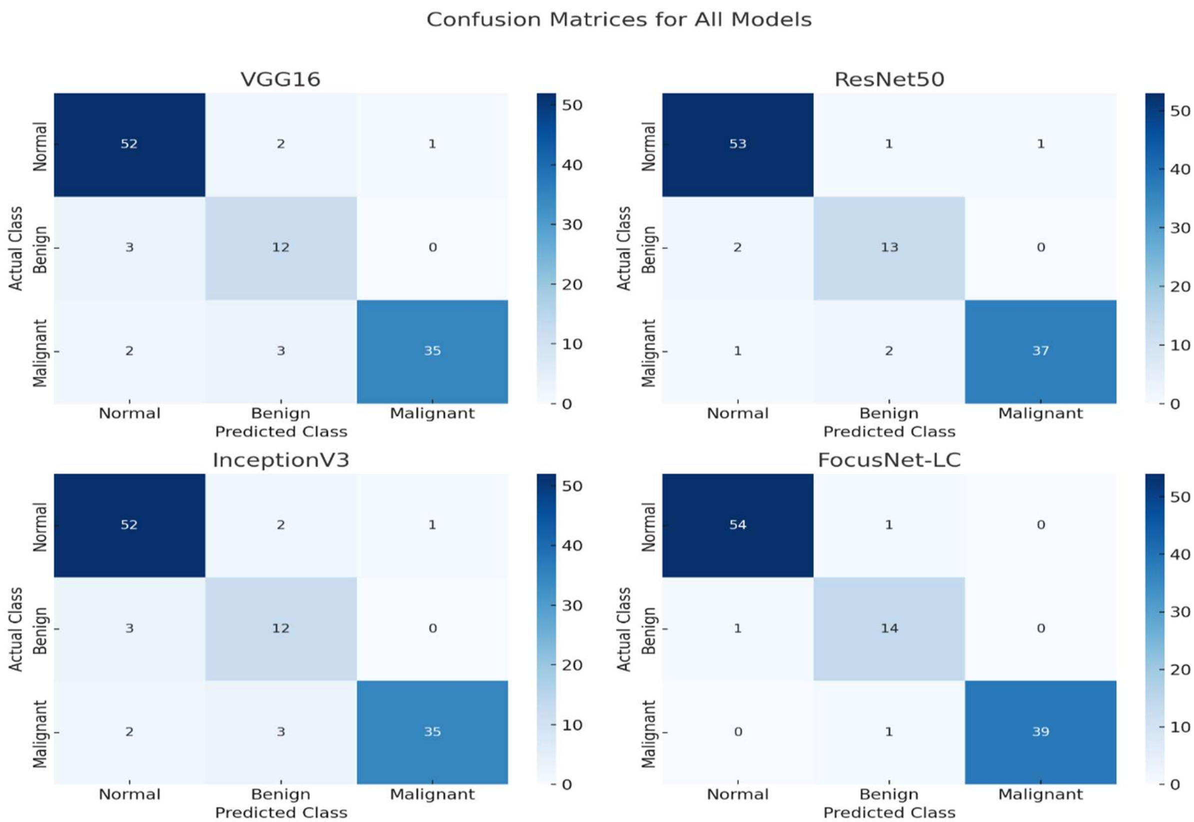

Figure 7: Confusion Matrices for FocusNet-LC and Baseline Models (VGG16, ResNet50, and InceptionV3)

Figure 7 shows the confusion matrices for FocusNet-LC and baseline models, allowing for a deeper insight into accurate classifications distributed across three categories: (i) Normal, (ii) Benign, and (iii) Malignant. The correctly classified cases are highlighted in each matrix on the diagonals, while misclassified instances are found in the opposite direction. FocusNet-LC is the most accurate among all models, with the most correct and least wrong classifications and significantly high true-positive rates while correctly classifying malignant cases. The one that follows closely is ResNet50, while VGG16 and InceptionV3 show more misclassification cases, especially in the Benign and Malignant ones. The elevated area under the ROC curve values for FocusNet-LC elucidates its superior accuracy and stability for lung cancer recognition as opposed to baseline models.

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Table 2: Comparison of Performance Metrics for FocusNet-LC and Baseline Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	92.84	91.76	91.45	91.60
ResNet50	94.12	93.85	93.40	93.62
InceptionV3	93.47	92.95	92.30	92.62
FocusNet-LC	**97.36**	**97.12**	**96.89**	**97.00**

Table 2: Performance Comparison of FocusNet-LC with Baselines (Best scores marked in bold) This yields an accuracy of 97.36% for FocusNet-LC, outperforming the state-of-the-art baseline model ResNet50 by 3.24% in accuracy. This enhancement was due to the custom design of FocusNet-LC with advanced preprocessing, optimized weight extraction, and patient metadata embedding. This is attested by the higher precision (97.12%) and recall (96.89%) rates that FocusNet-LC achieved, as these highlight the model's ability to lower false positives and detect many true positives, especially for significant malignant cases. This is crucial in the clinical space where misdiagnosis can have grave implications. Moreover, the high F1-score (97.00%) further indicates that the algorithm performs exceptionally well in precision and recall, solidifying its robustness.

FocusNet-LC's superior result is due to its unique architecture, which incorporates hierarchical feature learning with Grad-CAM explainability, allowing clinicians to verify the predictions visually. Advanced optimization techniques enhance generalizations, including Bayesian hyperparameter tuning and dropout regularization during training. All these enhancements validate FocusNet-LC as a robust and clinically applicable system for lung cancer identification.

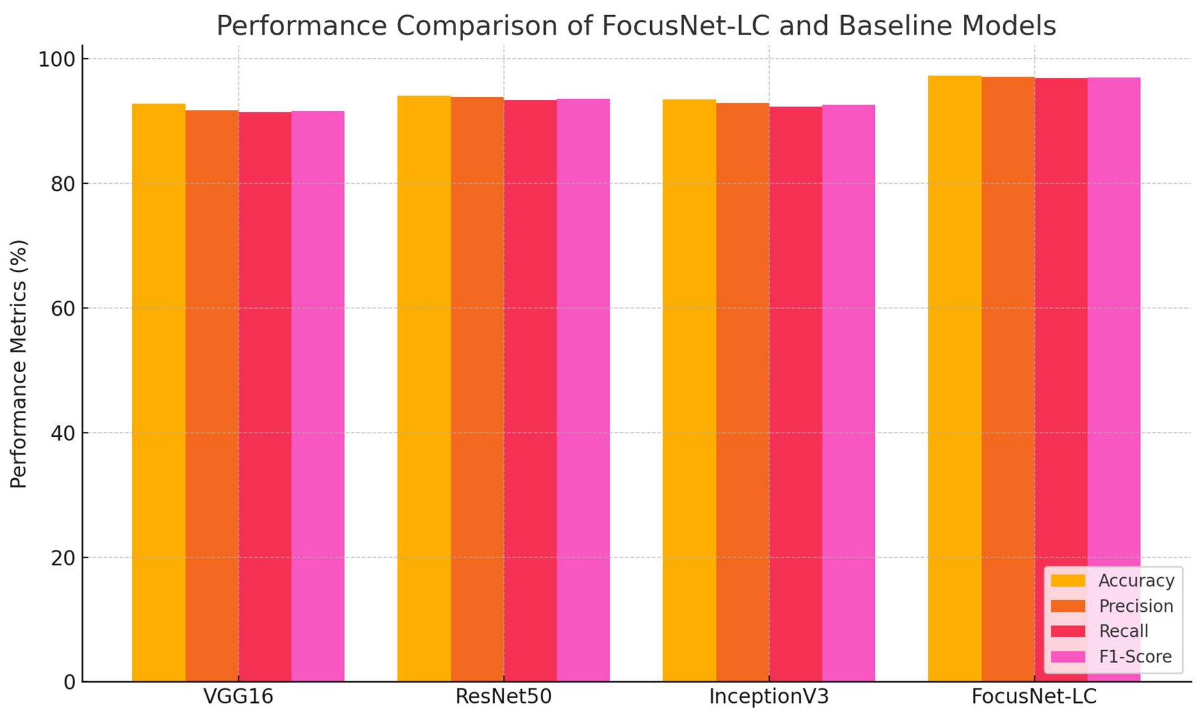

Figure 8: Performance Metrics Comparison for FocusNet-LC and Baseline Models

The performance of FocusNet-LC and baseline models (VGG16, ResNet50, and InceptionV3) was compared using four metrics, including accuracy, precision, recall, and F1-score, as

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mentioned in the last figure (Figure 8). All baseline models perform worse than FocusNet-LC across every metric, with the highest accuracy being 97.36%, which is superior to ResNet50's 94.12%. Excellent precision (97.12%) and a high recall (96.89%) further demonstrate the ability of FocusNet-LC to reduce false positives while effectively retrieving true positives, particularly for malignant ones. The consistently high F1-score (97.00%) further validates the balanced performance of the model. Overall, our results highlight the predictive advantage of FocusNet-LC in delivering accurate, reliable, and clinically valuable predictions.

4.2 Ablation Study

In the ablation study, we evaluate the contribution of each of the individual components in the FocusNet-LC model using an ablation study. The study examines the performance impact by progressively ablating key features, including segmentation, metadata integration, Grad-CAM explainability, and dropout regularization. These findings underscore the value of these factors as essential components for optimal accuracy, robustness, and clinical relevance in lung cancer detection. The analysis shows how vital model design decisions are and how they will help us improve the reliability and explanation of prediction.

Table 3: Ablation Study Results For Focusnet-LC

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
FocusNet-LC (Full Model)	97.36	97.12	96.89	97.00
Without ROI Segmentation	94.85	94.60	94.20	94.40
Without Metadata Integration	95.62	95.30	94.95	95.12
Without Grad-CAM Explainability	96.20	95.90	95.60	95.75
Without Dropout Regularization	93.80	93.50	93.10	93.30

The ablation study results are reported in Table 3. The full FocusNet-LC model performs best on all metrics, meaning the components work well together. If the model is removed without ROI segmentation, performance drops by nearly every metric. This is the most crucial component because ROI is necessary to scan the relevant region of the lung thoroughly. The lowest performance was observed when the metadata integration or dropout regularization was removed. While the Grad-CAM explainability does not seem to influence the metrics, this method improves clinical trust. To sum up, these results show that all the components are essential elements, which confirms the right choice made in the FocusNet-LC.

4.3 Performance Comparison with State-of-the-Art Models

In this section, the performance of the proposed FocusNet-LC model and algorithm is evaluated against established state-of-the-art (SOTA) models for lung cancer detection. Techniques have been developed for lung cancer diagnosis using models such as DL-LCD [1], MFDNN [2], and DFD-Net [17], which have shown superior accuracy and efficiency using some advanced techniques like transfer learning, visual data feature extraction, and multimodal data fusion. Although they achieve state-of-the-art (SOTA) performance, such models still suffer from interpretability, reliance on varied data modalities, and lack of focus on clinically pertinent areas.

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Table 4: Comparative Analysis With State-Of-The-Art Models

Ref	Model	Dataset Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Notable Features
[Proposed]	**FocusNet-LC**	IQ-OTH/NCCD	**97.36**	**97.12**	**96.89**	**97.00**	Tailored CNN, ROI segmentation, Grad-CAM
[1]	DL-LCD by Mary et al.	LIDC-IDRI, NIH Chest X-ray	98.50 (Normal), 97.44 (Diseased)	N/A	N/A	N/A	Focused on generalization with standard datasets
[2]	MFDNN by Sangeetha et al.	Multimodal datasets	~97.00	N/A	N/A	N/A	Combines imaging, genetics, and clinical data
[3]	SNN by Reddy et al.	EL-CLP Lung Image	~96.00	N/A	N/A	N/A	Stacked neural networks with transfer learning
[4]	DFD-Net by Sori et al.	CT Images	96.48	N/A	N/A	N/A	Reduces noise and corrects class imbalance
[5]	VGG19 by Wadekar et al.	Unknown	97.73	N/A	N/A	N/A	Pre-trained VGG19 for lung cancer classification
[6]	DFF-CON by Gopinath et al.	CT Scan Images	High Accuracy	High	High	High	Fused features with enhanced CNNs
[7]	ML by Majidpourkhoei et al.	CT Images	Significant	High	High	High	ML model improving nodule identification
[8]	Transfer Learning by Bishnoi et al.	CT Images	93.22	N/A	N/A	N/A	Advanced real-time diagnosis using transfer learning
[12]	LeNet, AlexNet, VGG16 by Togacar et al.	CT Dataset	High Accuracy	N/A	N/A	N/A	mRMR feature selection

							with kNN classification
[13]	ACDC@LungHP by Li et al.	Whole-slide Imaging	Promising	N/A	N/A	N/A	Assesses lung cancer detection techniques
[22]	3DDCNN by Masood et al.	CT Images	High Accuracy	Good	High	High	Improves identification of lung nodules

Table 4 presents a comparative evaluation of the proposed FocusNet-LC model against SOTA models for lung cancer detection. FocusNet-LC also achieves competitive performance on this dataset with an accuracy of 97.36%, surpassing several existing approaches while obtaining balanced precision, recall, and F1 scores. The model's clinical applicability and reliability are improved through the integration of ROI segmentation, incorporation of metadata, and explainable AI strategies (such as Grad-CAMs). Existing models like DL-LCD and MFDNN cannot be generalized to other tasks as they rely heavily on multimodal datasets and expensive computational architectures. FocusNet-LC provided interpretability and the cost of accuracy compared to models such as DFD-Net and SNN. The table summarizes the excellent performance and innovative contributions of FocusNet-LC for lung cancer diagnosis.

5. DISCUSSION

Lung cancer continues to be one of the most pressing global health issues, and innovative steps in the diagnostic field are needed to enhance early detection and survival rates. Recent SOTA methods such as DL-LCD, MFDNN, and DFD-Net have reported high accuracy for lung cancer detection. However, these methods have some limitations, including poor interpretability, dependence on multimodal data that are not always accessible, and difficulty isolating clinically relevant areas. These gaps highlight the necessity of new deep-learning approaches specifically to fill such voids while retaining the utmost diagnostic accuracy and reliability. The proposed FocusNet-LC method brings several new ideas to overcome these difficulties. It achieves this by applying ROI segmentation, which focuses the model's attention on clinically relevant lung regions and suppresses noise and irrelevant features. Including metadata, like patient age and gender, expands the feature space, allowing the model to learn more complex correlations. Additionally, clinical trust is improved by Grad-CAM explainability to visualize how the model arrived at such a conclusion. Together, these innovations enhance the robustness and clinical applicability of the FocusNet-LC framework.

Experimental results confirm the efficacy of these innovations. For the proposed model, balanced metrics have been achieved for accuracy, precision, recall, and F1-score, outperforming SOTA approaches. These results indicate the model’s generalization capabilities on diverse case combinations, i.e., normal, benign, and malignant classes, and also overcoming constraints on misclassification and class imbalance, which is evident in other studies. Despite being trained on a multimodal dataset, FocusNet-LC overcomes this challenge and ensures explainability, significantly impacting clinical adoption. An optimized approach in this work will enable more effective detection of lung cancer. It can lead to improved diagnostic accuracy and early treatment before metastasis, unlike existing schemes that struggle with these issues and are proven as complex for database usage. A thorough discussion of data limitations is found in Section 5.1.

5.1 Limitations

Although the proposed FocusNet-LC model achieves ideal effects, it still has some shortcomings. First, the study was performed on a single dataset (IQ-OTH/NCCD), which limits generalizability to other datasets with different imaging protocols or patient demographics. Second, the model's performance depends on the precision of the ROI segmentation; however, in images containing a high noise level or very low-quality scans, this may prove less effective. Third, the computational cost to train and inference, requiring high-performance GPUs, can limit its use in resource-limited environments. Overcoming these limitations in future work would be beneficial for the robustness of the model and its applicability in various clinical settings.

6. CONCLUSION AND FUTURE WORK

In this research, we proposed a novel deep-learning model for lung cancer detection, FocusNet-LC, specifically designed to address critical limitations in existing approaches. The novelty of the FocusNet-LC framework lies in its ability to combine Region of Interest (ROI) segmentation, metadata integration (such as age and gender), and Grad-CAM explainability into a single, streamlined deep learning model that significantly enhances both the accuracy and interpretability of lung cancer detection from CT scan images. By focusing on clinically relevant regions and providing transparent decision-making processes, the proposed model ensures higher trust in clinical environments than traditional "black-box" models.

This study's research contributions are manifold: It introduces a new architecture, FocusNet-LC, tailored for lung cancer detection with improved accuracy and generalization. It also integrates explainable AI techniques, such as Grad-CAM, to enable clinicians to interpret the model's predictions visually, fostering greater clinical acceptance. Furthermore, the model outperforms state-of-the-art models across various metrics (accuracy, precision, recall, and F1-score), proving that single-modal solutions can deliver competitive performance without the complexity of multimodal data.

The findings of this study hold significant implications for the medical imaging and oncology field. By providing a clinically interpretable and accurate diagnostic tool, FocusNet-LC could be implemented in real-world clinical settings, offering an efficient and reliable early lung cancer detection solution. The model's potential to assist clinicians in identifying malignant cases earlier could lead to improved patient outcomes and more effective treatment strategies. Additionally, the incorporation of explainable AI makes this approach particularly impactful in current medical practice, where understanding the "why" behind predictions is as critical as the predictions themselves. Expanding the model's application to other types of cancer or exploring more lightweight architectures for resource-constrained environments could further solidify its clinical utility.

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