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Enhanced Lung Cancer Detection Using Custom Convolutional Neural Network with Comparative Analysis of Deep Learning Models

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Abstract

Lung cancer dominates cancer-related deaths across the globe, and its early diagnosis is the only way for effective treatment. The diagnosis of lung cancer has improved using CT scans along with deep learning techniques. The custom CNN architecture is proposed to classify chest Computed Tomography (CT) scan images into three categories namely normal, benign and malignant lung tissue. For the evaluation of the proposed CNN architecture, various classification metrics have been used, considering their performance with VGG16 and ResNet50, the other two advanced deep learning models. It was concluded that the proposed custom CNN outperformed VGG16 and ResNet50 with an accuracy of 97.6%, precision rate of 98%, recall rate of 98%, F1 score of 98% and proved to be effective as a model for accurate classification even in cases presenting nodules of smaller size. These results showed the potential of deep learning approach of custom CNNs for detecting lung cancer with high accuracy and automation, thus offering a promising tool to support radiologists in further early diagnosis and treatment planning.

Keywords: *Automated Diagnosis; Convolutional Neural Network (CNN); Early Detection; Lung Cancer; Medical Imaging;*

1. Introduction

Lung cancer is one of the most prevalent and deadly cancers worldwide, accounting for high proportion for tumor-related deaths [1]. Early detection is the key to treating lung cancer, which would significantly improve the possibility of successful therapy and patient survival. Classical methods for diagnosis including manual chest CT scan examination, are very time- consuming and liable to human error and depend greatly on the radiologist's experience. Recent deep learning and computer vision development has provided many tools for automatic analysis of medical image. Among various approaches, Convolutional Neural Networks (CNNs) has shown better performance in tasks like image classification, object detection as well as feature extraction. These networks are effective in detecting abnormalities from medical images [2]. CNNs can identify difficult pattern to detect small nodules or early-stage lesions by learning hierarchical representation from raw pixel format. During 2022, lung cancer was ranked as the top three of the common cancer, leading to 7.8% of new cases across the world [3]. In Bangladesh, Lung cancer caused 12,063 deaths, which is ranked second for causing of overall cancer-related deaths [3]. Men are major victims due to higher smoking rates compared to women [3]. The limited access to diagnostic tools, especially in rural areas, complicates the treatment effort in the country [4]. Early detection is so important because most cases are diagnosed at advanced stages. Recent advancements in medical imaging have led to the use of machine learning and deep learning techniques for automated and early identification of this disease. However, most of the traditional approaches show moderate success as their performance was limited by model complexity and sensitivity. This led to the proposal of the custom CNN approach and the study of its superiority over widely used pre-trained architectures which includes VGG16 as well as ResNet50 for validating its performance using various classification metrics. The results indicate that custom CNN not only achieves higher classification performance but also behaved as a lightweight as well as an efficient solution for automated detection. The contributions of this study are threefold:

- Developed a custom Convolutional Neural Network architecture to improve the lung

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cancer detection accuracy.

- Effective preprocessing and data augmentation to improve results on limited datasets.
- Demonstrated how the model outperformed others when compared to standard pre-trained architectures, underlining its potential for clinical adoption for automated diagnosis and early identification of the cancer.

The remainder of the paper is organized as follows: Division II briefs about the literature survey on existing lung cancer detection techniques. Division III explains about the dataset, preprocessing procedures, the methodology employed in this study. Finally, Division VI concludes paper and provides potential areas for future enhancement.

1.1. Related Works

Sub Some researchers have used deep learning and proposed diverse architectures which are aimed at enhancing both accuracy and reliability of detecting lung cancer. Sadia Zannat Reem et al. proposed a custom EfficientNetB7 model using chest CT scan images achieving 96.48 accuracy, 96.25 precision and recall Score [5]. Shalini and Vigneshwari [6] introduced model to detect cancer using Hybrid Neural Network framework which integrates 3D-CNN with RNN models. Their approach achieved 95% accuracy when tested on the LUNA 16 dataset. Similarly, Humera Shaziya [7] assessed multiple architectures for diagnosing cancer which achieved notable performance 98.13% dice coefficient for segmentation, 93.58% accuracy for nodule classification using LIDC-IDRI, and 98% accuracy for nodule classification with IQ-OTH/NCCD dataset. Shashikala et al. [8] addressed the issue of early-stage lung cancer diagnosis using CNN models trained on CT datasets and recorded high accuracy, low loss, and an AUC of 94.5%. Radhika et al. [9] presented work comparing different classical algorithms on two datasets. They recorded an accuracy of 96.9% with Logistic Regression and 85.7% with Decision Tree on the UCI dataset, while SVM recorded 99.2% accuracy on the data.world dataset. Shaziya et al. [10] proposed framework called LungNodNet using the LIDC-IDRI to classify lung nodules achieving accuracy of 93.58%. Yahya et al. [11] improved CNN-based lung cancer classification by incorporating CBAM. This increased the model performance of their best model by 7.3%. Combining VGG16 with SVM achieved highest accuracy of 83.49%. Al-Shouka and Alheeti [12] developed a probabilistic deep 2D CNN framework to classify the CT scan images, recording 92% recall, 87% sensitivity, 87% specificity, 86% overall accuracy, and 91% precision. M. Phankokkruad [13] utilized transfer learning on VGG16, ResNet50V2, and DenseNet201 architectures for classifying lung cancer images, recording an accuracy of 62%, 90%, and 89%, respectively, with better validation accuracy of 91% when an ensemble combination of the models was employed. Mamun et al. [14] put forward a custom Convolutional Neural Network (CNN) for detecting the disease, achieving 92% accuracy, 98.21% AUC, and 91.72% recall. However, authors stated that further enhancement in model robustness and medical reliability was needed. Finally, Al-Shouka and Alheeti [15] examined hybrid deep learning models that combined MobileNetV2 with CNN-based transfer learning techniques, including ResNet, VGG16, and Xception architectures, for medical image analysis. Their model attained accuracy of 94%; however, further studies were recommended to improve the generalization of such approaches across diverse medical datasets.

2. Methodology

The proposed research focuses on developing custom Convolutional Neural Network for classifying lung cancer from CT scan images into three categories: Normal, Benign and Malignant lung tissue. The workflow consists of four major steps which is dataset collection, image preprocessing, CNN model design, and model training and evaluation. The system’s overall framework is illustrated in Figure 1 which provides systematic progression from data preparation to model optimization, ultimately resulting in a robust and reliable diagnosing lung cancer. The custom layer includes 7 conv blocks with each block having different layers with increasing level of identifying hidden patterns from the image. In addition, two models, ResNet50 and VGG16 which are pre-trained networks are trained to compare the effectiveness of the proposed model across deeper networks.

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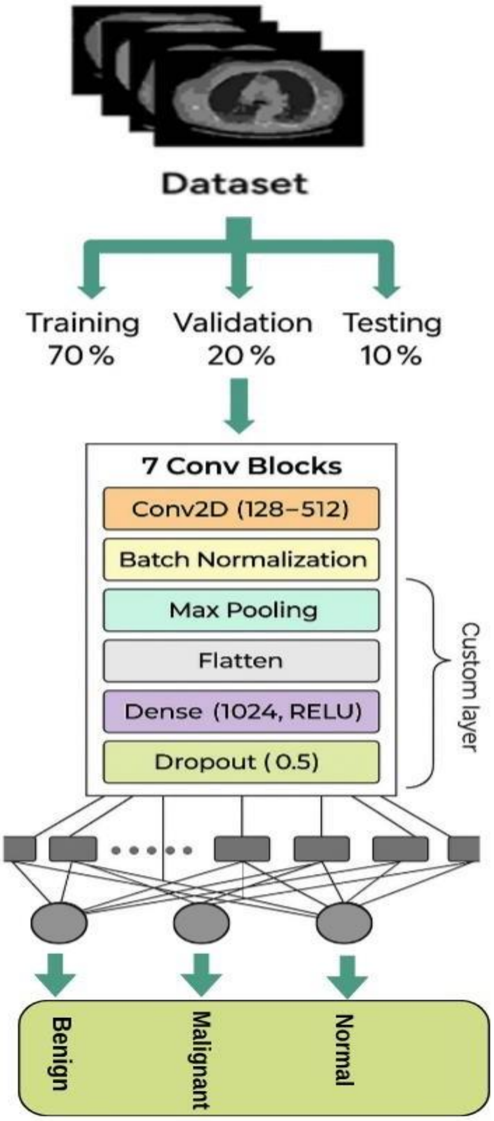

Figure 1 **Research Methodology**

2.1.Data Collection

The proposed research utilizes the IQ-OTH/NCCD Lung Cancer Dataset, which is widely used in medical image analysis research [16]-[18]. It contains chest CT scan images that are collected from multiple patients and is organized into three categories which are Normal, Benign and Malignant lung tissues. It has a total number of 1,097 images, where 561 are malignant, 416 are normal, and 120 are benign samples. Each image represents a 2D CT slice in grayscale format and captures different features related to nodules in the lungs, which may lead to cancer. It is developed to facilitate research in automated diagnosis, containing a fair amount of all stages of cancer and no cancer cases. High-resolution computed tomography images were captured using standard imaging protocols thereby ensuring consistency and clinical reliability. This dataset was selected because it is easily available and can be used for variety of cases, and it is suitable for deep learning-based classification tasks in lung cancer detection. Figure 2 represents sample images which belongs to two major classes of the dataset.

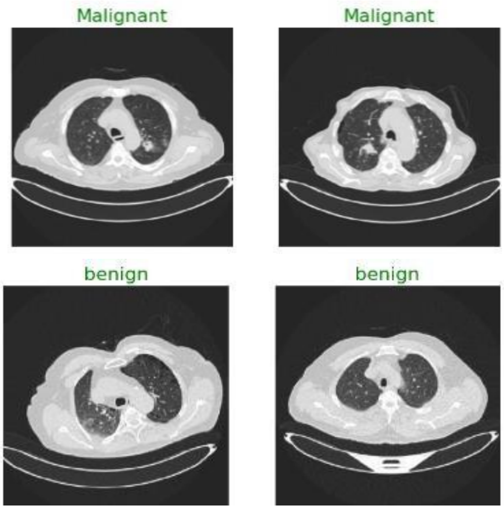

Figure 2 **Representative CT Scan Images Used in This Study**

2.2.Data Pre-Processing

The input images were initially resized into 224 × 224 pixels and then normalization was carried out to put them in the range [0, 1] before training for consistency and faster convergence. The data augmentation was done to enhance generalization and reduce overfitting by including random rotations, flips, shifts, brightness adjustment, and shearing. A ratio of 70:20:10 was adopted to build the training, validation and testing subsets, ensuring that all the classes are balanced. These steps enhanced the effective size of dataset and the robustness of CNN model. It also gathered statistics about the images such as image size, and model, which were kept constant across the dataset.

2.3. Proposed Custom CNN Model

This study introduces a custom Convolutional Neural Network (CNN) for categorizing input images into three classes which are Normal, Benign and Malignant. An architecture is designed in such a way

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that hierarchical features are extracted from the input images while keeping computational efficiency in consideration. The network begins with a layer of Conv2D with a kernel size of 8×8, stride of 3×3, and 128 filters. It is then followed by batch normalization for stabilizing the learning. Then there are several convolution blocks, each with a multiple Conv2D layers having filter sizes increased from 256 to 512, ReLU for the activation, and batch normalization. Max-pooling layers introduced to reduce the dimensionality while preserving the important features. To prevent the neural network from overfitting some neurons were dropped out at the rate of 0.5. This layer was inserted prior to the fully connected layers. The output from this layer is then flattened and fed into two dense layers which consists of 1024 neurons and ReLU activation. Then a layer of Softmax is added that provides the probability score for each class. Finally, the compilation of the model was done using categorical cross-entropy as the objective function and stochastic gradient descent with 0.001 learning rate for parameter optimization. Learning rate scheduling and early stopping were introduced to optimize the performance and to prevent the network from overfitting. The proposed architecture is designed to effectively capture both low level and high- level features for accurate and robust classification of input images.

2.4. Model Training

The network was trained on preprocessed input images over 10 epochs with a batch size of 4. The network parameters were optimized using the Adam optimizer with loss function as categorical cross-entropy. To improve training stability and suppress overfitting, techniques such as early stopping and adaptive learning-rate scheduling have been employed. To evaluate performance various metrics were used to calculate on the test set. The optimized hyperparameters are tabulated in Table I.

Table 1 Hyper Parameters for Model Training

Hyperparameter	Value
Base Model	Custom CNN
Input Shape	(224, 224, 3)
Dense Layer Units	128
Dense Layer Activation	ReLU
Batch Normalization	Enabled
Dropout Rate	0.5
Output Dense Layer Units	3(Number of Classes)
Output Dense Layer Activation	Softmax
Compiler	Stochastic Gradient Descent (SGD)
Loss	Categorical Cross entropy
Metrics	Accuracy
Epoch	10
Batch size	4
Total Parameters	15,610,499
Trainable Parameters	15,604,099
Non- trainable Parameters	6,400

3. Experimental Results

The experimental analysis was performed to validate the proposed custom CNN model against two architectures which are VGG19 and ResNet50. The performance metrics such as accuracy, precision, recall, and F1-score was calculated for each architecture in order to access the efficiency of the model across the three classes of the lung CT images.

Table 2. Testing Accuracy and Loss

Model	Testing Accuracy (%)	Testing Loss(%)
Custom CNN	97.6	0.092
Copper	68.8	0.670
Graphite	90.8	0.828

Table 2 provides the comparison between custom CNN and the two widely used transfer learning architectures which are VGG16 and ResNet-50. From this, it can be understood that the Custom CNN has achieved the highest test accuracy of 97.6% with minimal loss of 0.092. This surpasses the performances of VGG16 with 90.8% accuracy and loss of 0.828 and ResNet-50 with 68% accuracy and loss of 0.670. The findings further reinforce the architecture's capability to get more discriminative features for providing better generalization compared to deeper pretrained networks.

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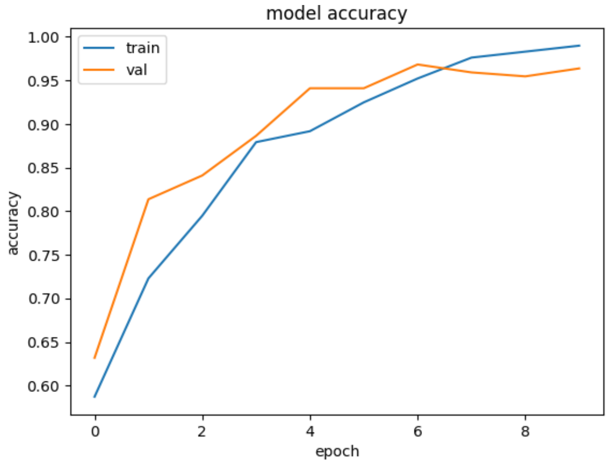

Figure 3 Model Accuracy

Table 3 Classification Metrics of Custom CNN

Class Name	Precision	Recall	F1-score
Malignant	99.00	100.00	100.00
Normal	94.00	99.00	97.00
Benign	100.00	82.00	90.00
Weighted Average	98.00	98.00	98.00

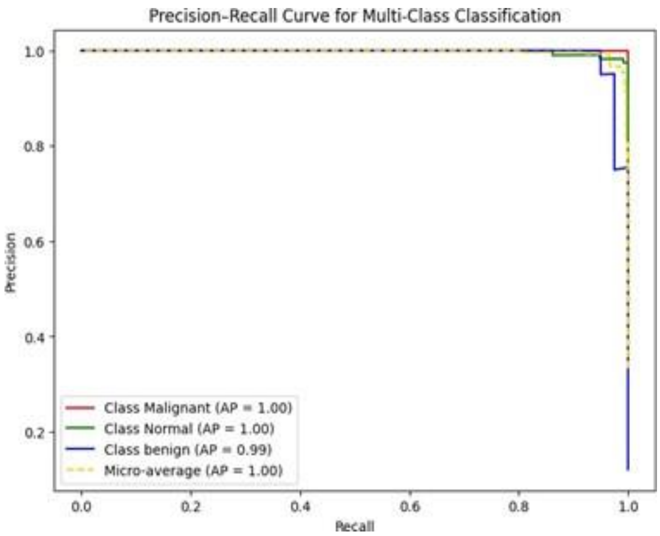

Figure 4 Loss Curves

Table 3 provides the summary of performance of the custom CNN architecture. The results show consistent performance across the classes. The Malignant achieved which near-perfect detection, 0.99 precision and perfect recall 1.00, while the Normal class has a strong balance with 0.94 precision, 0.99 recall. The Benign class achieved a precision of 0.99 and 0.82 recall showing only minor variation in sensitivity. In general, the model attained strong classification performance of 0.98 which shows high reliability and generalization capability.

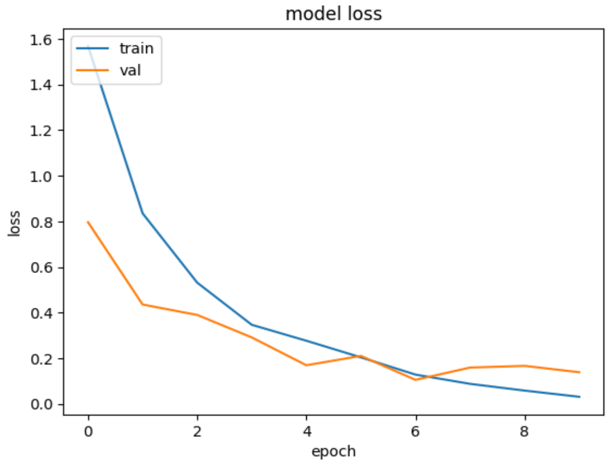

Figure 5 Training and Validation Performance of the Custom CNN Model

Figure 3 shows the accuracy and loss curves of the custom CNN architecture. Figure 3(a) presents accuracy trend that increases consistently for both the phases and remains steady after reaching around 97–98%, which indicates good learning. Second, the loss curves in Fig. 3b decrease consistently and stay at the minimum value which is approximately 0.09; this shows proper convergence of the model with less overfitting. Overall, these trends confirm that this model generalizes well and effectively learns important features from the dataset.

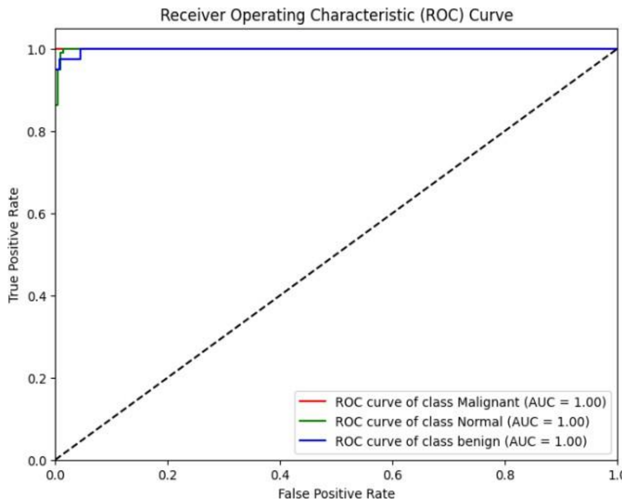

Figure 6 ROC-AUC Curve of the Custom CNN

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Figure 4 depicts the ROC curves of the custom CNN model across all three classes. The AUC using this model was 1.0 for the three classes, showing that it achieves perfect classification performance. This proves the model's strong ability in identifying important patterns and in classifying different categories of lung cancer.

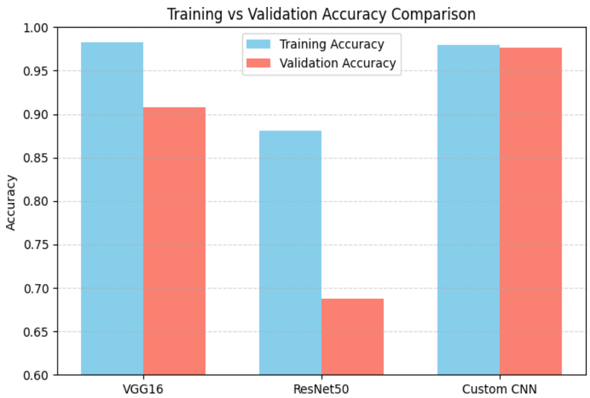

Figure 7 Class-Wise Precision-Recall of the Custom CNN model

The PR curves of this model is illustrated in Figure 5. These curves show the tradeoff between precision and recall and highlight the strengths of this model in identifying actual positive instances while reducing false positives. The proposed model presents classification performance near-optimal across all categories, reaching PR-AUC

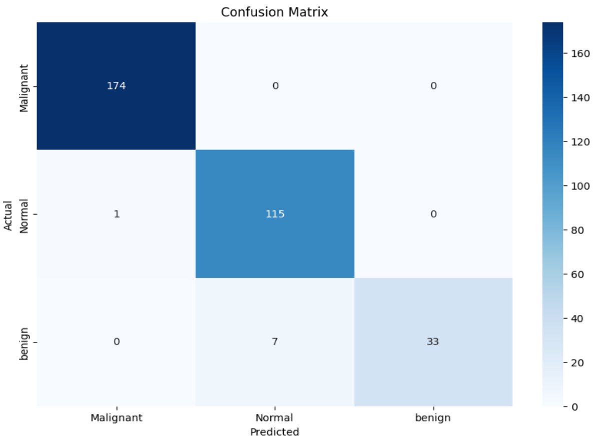

Figure 8 Confusion Matrix of Custom CNN

values of 1.0, which denote extremely strong predictive power. In summary, all these results confirm that the proposed approach is effective in identifying Normal, Benign, and Malignant lung tissue classes with high accuracy. Figure 6 presents the confusion matrix obtained for the proposed Custom CNN architecture. From this matrix, it can be identified that the Malignant class was perfectly classified with 174 correct predictions and no misclassifications. The Normal class had 115 correct predictions, with only 1 misclassified as Malignant. The Benign class achieved 33 correct predictions, with 7 misclassified as Normal. This distribution underlines that the model differentiates Malignant and Normal CT scans perfectly and confuses only few Normal and Benign images. Overall, the confusion matrix confirms the high reliability and discriminative power of the model across all classes. Three models namely Custom CNN, VGG16, and ResNet50 were put to the test with the same experimental settings for the same dataset. Figure 7 shows comparison of accuracy of the three models which have been plotted in the form of a graph. Unlike deeper architectures such as ResNet50 and VGG16, which may overfit and be computationally expensive for small medical datasets, Custom CNN attains a favorable balance between classification performance and computational efficiency. The architecture of the model is also lightweight with fewer parameters and its custom nature gives full control in adding layers and building the model. The model provides high accuracy with reduced model complexity as compared to pretrained models. The outcomes of other classification metrics accounts for reliable classifications in all categories with small misclassification as seen in the confusion matrix.

4. Discussion

The experimental investigation reveals that the custom CNN architecture exhibits strong performance by attaining an accuracy of 97.6% with good differentiation among the three classes of this dataset. The results achieved faster convergence and improved generalization by optimizing the kernel size, stride, and batch normalization layers. This is further supported by the ROC and precision–recall curves with an AUC value of 1.0 for all classes, representing good separability and robustness. These outcomes underscore the proficiency of the proposed model as a reliable tool for automatic screening of lung cancer, capable of assisting clinicians in early diagnosis and reducing mistakes in manual

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diagnostic. The comparison of the performances for the three architectures reveals that, while pre-trained models like ResNet50 and VGG16 perform very well on large-scale datasets, their deeper structures overfit and are much more expensive in terms of computations on smaller medical datasets. In contrast, the Custom CNN shows that a shallow model but optimized for the task at hand can achieve a higher accuracy with less computational training time and resource consumption, thereby making it more deployable in healthcare environments that have limited computational infrastructure. These findings thus shows that the proposed model can act as a robust diagnostic aid for radiologists for early detection while reducing diagnostic subjectivity. This study, therefore, provides evidence that customized deep learning architectures have the potential for outperforming standard transfer learning models in domain-specific medical applications.

Conclusion

This study proposed a custom Convolutional Neural Network (CNN) for accurate detection of lung cancer using the IQ-OTH/NCCD CT scan dataset, effectively categorizing images into Normal, Benign and Malignant classes. The model achieved an accuracy of 97.6%, performing better than VGG16 and ResNet50, thereby demonstrating its effectiveness and robustness. The high precision, recall, and F1-score with an average of 98% confirms the model's strong generalization and reliability. The confusion matrix further demonstrates consistent predictions across all classes, while ROC and Precision– Recall curves (AUC = 1.0) highlighted its excellent performance. Overall, the custom CNN offers a lightweight and efficient diagnostic framework suitable for real-world medical image analysis. Future research would include broadening the dataset for improved generalization and integrating explainable AI (XAI) techniques. Moreover, real-world clinical evaluation and the development of an AI-assisted diagnosis will also facilitate the translation of this research into healthcare applications

Table 4 Comparison of Approaches Used for Lung Cancer Detection On Different Dataset

Article	Methods	Dataset	Accuracy	Recall	Precision	F1 Score
Mamun et al. [14] (2023)	CNN, Inception V3, Xception, ResNet-50	Chest CT scan images	92%	91.72%	92.30%	92.01%
Al-Shouka and Alheeti [15] (2023)	MobileNetV2, Transfer Learning	Chest CT scan images	94%	Not reported	Not reported	Not reported
Al-Yasriy et al. [17],2020	Alex Net	IQ-OTH/NCCD	93.45%	95.71%	Not reported	Not reported
Kareem et al. [18], 2021	SVM- classic ML baseline	IQ-OTH/NCCD	89.88%	97.14%	98.55%	97.84%
AL-Huseiny & Sajit [19] ,2021	Transfer learning with GoogLeNet (TL)	IQ-OTH/NCCD	94.38%	95.08%	Not reported	Not reported
Our Work	**Custom CNN**	**IQ-OTH/NCCD**	**97.6%**	**98%**	**98%**	**98%**

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