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DETECTION OF LUNG CANCER THROUGH COMPUTED TOMOGRAPHIC IMAGES USING DEEP LEARNING MODELS

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Abstract

Lung cancer maintains its positions as a leading cause of worldwide cancer fatalities so there remains an immediate requirement for dependable and fast diagnostic techniques. Research presents a sophisticated deep learning system which applies 5-fold cross-validation to EfficientNet-B0 for accurate CT image-based lung cancer classification. We integrated Chest CT-Scan Images and IQ-OTHNCCD datasets from Kaggle into our research which included public domain images numbering 1,415 total images. The research then utilized complex preprocessing and augmentation methods for performance enhancement. The methodology merges median noise reduction with broad data augmentation to prevent overfitting and includes EfficientNet-B0 as the classification CNN. The proposed framework reached maximum validation accuracy of 99.32% within Fold 3 when validated through 5-fold cross-method while maintaining an average accuracy of 97.43% across all folds. This method achieves superior performance compared to state-of-the-art techniques through comprehensive evaluation measurements that demonstrate precision at 97% and the other attributes at 98% and 98% and 97.9% respectively. The proposed framework demonstrates strength as an efficient method for detecting early lung cancer which shows promise to boost clinical decision-making and patient outcomes.

Keywords: Lung Cancer Detection, Deep Learning, EfficientNet-B0, K-Fold Cross-Validation, CT Imaging, Medical Image Analysis

INTRODUCTION

Lung cancer stands as one of the deadliest diseases that exists worldwide because patients commonly detect their condition too late. Early detection of malignant lung nodules by means of computed tomography scans remains essential for enhancing survival rates since it allows for prompt intervention using surgical procedures and targeted treatments. Over the past decade, large-cohort clinical studies have established that low-dose CT screening reduces lung cancer mortality, largely owing to increased diagnosis and treatment at earlier disease stages. These data have led to recommendations that individuals with a high risk of lung cancer undergo screening in several economically developed countries and increased implementation of screening worldwide [1]. CT scans show early-stage nodules in a challenging manner which makes radiologists using conventional diagnostic methods experience problems with inter-observer variability while completing time-consuming manual analyses.

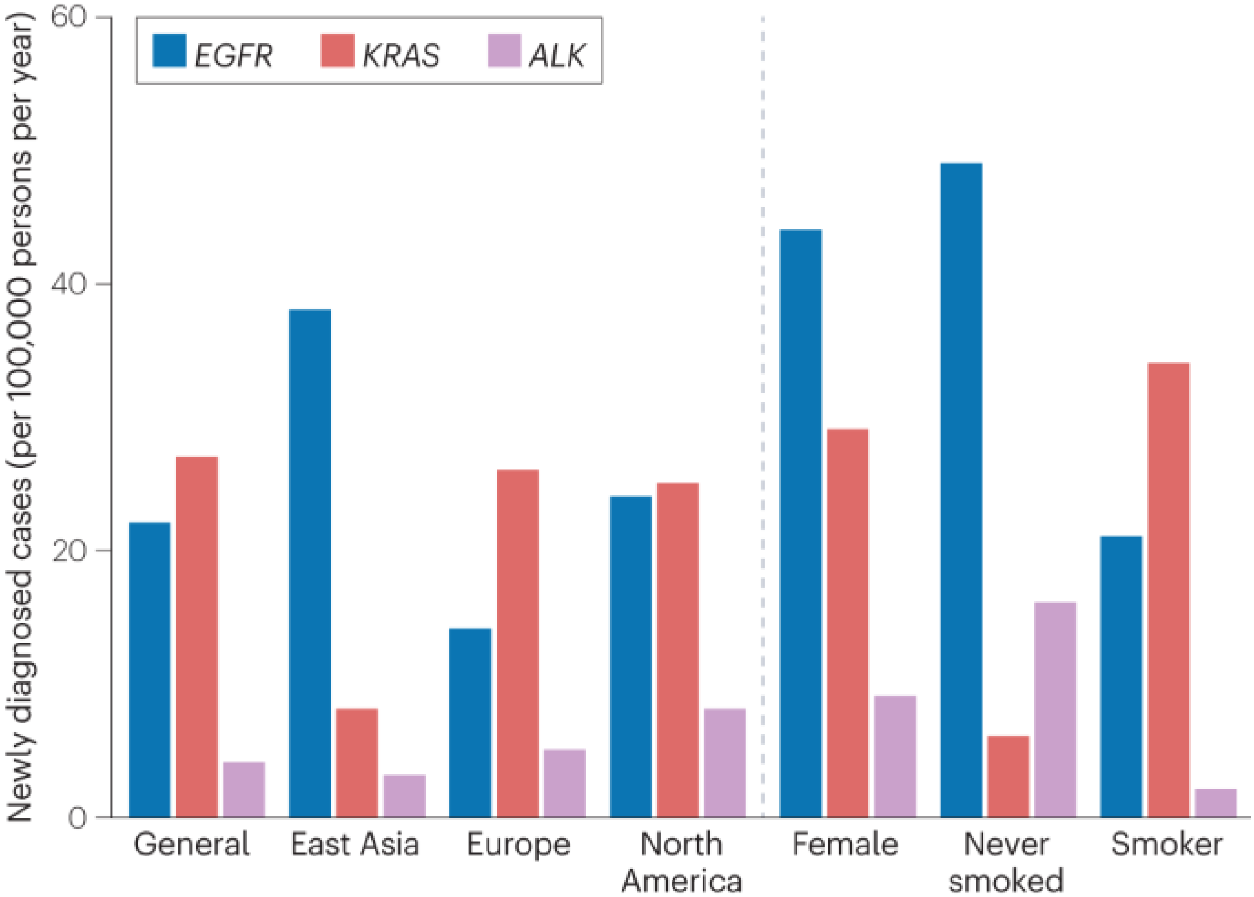


Figure 1: New Diagnosed cases Worldwide 2023 [1]

Medical imaging is undergoing a transformation because deep learning forms part of artificial intelligence which provides automated precise scalable solutions. Convolutional neural networks (CNNs) [2] demonstrate exceptional success in medical image pattern recognition since they outperform human diagnostic abilities in specific medical procedures. The achievement of absolute accuracy in lung cancer identification faces challenges because medical imaging typically contains insufficient data points and unequal distribution between classes [23].
A new deep learning system designs to overcome these research hurdles is presented in this work. Our solution includes EfficientNet-B0 [3] as its core CNN architecture because of its proven efficiency in balanced depth and width and resolution scaling while operating through 5-fold cross-validation for model generalization. The dataset consists of 1,415 CT images divided into Normal, Benign and Malignant groups that derive from Chest CT-Scan datasets [4], [5] and IQ-OTHNCCD [6] sources [21-22]. Image preprocessing through median filtering when combining with aggressive augmentation methods increases dataset size and minimizes overfitting effects. The research methodology delivers 99.32% maximum accuracy in Fold 3 and maintains an average accuracy of 97.43% across all folds while surpassing the results of multiple present-day techniques.

1 Related Work

Advanced research on CT-based lung cancer detection addresses two main stages: identifying possible nodule discoveries while reducing numbers of errors. The paradigm has shifted in lung cancer detection through CT imaging because CNNs which learn features directly from raw data surpassed previous techniques such as support vector machines and decision trees.

A comprehensive performance comparison was conducted within the framework of conventional Convolutional Neural Networks (CNNs). Rigorous image preprocessing techniques, including affine transformation and Gaussian noise, were employed. The proposed approach achieved a validation accuracy of 99%, demonstrating the effectiveness of the preprocessing methodology in reducing model complexity. The comparison further revealed that the suggested preprocessing method resulted in a higher F1-score of 99%, confirming the robustness and accuracy of the approach [7].

research leveraged two distinct datasets: the IQ-OTH/NCCD dataset, which contains benign, malignant, and normal cases, and another dataset comprising three carcinoma classes along with a normal class. When applying a Convolutional Neural Network (CNN) architecture in VGG-16 using only the dataset with three classes, the experiment achieved a test accuracy of 89% with relatively low computational power [21]. Furthermore, by implementing ensemble learning techniques through a majority voting architecture combining VGG-16, ResNet50, InceptionV3, and EfficientNetB7, the model not only classified CT scans as malignant, benign, or normal but also distinguished between different types of lung carcinomas. This ensemble approach outperformed all other trials, achieving a test accuracy of 92.8% [8].

An extensive review of the literature was conducted to evaluate existing methodologies, revealing a gap in the application of advanced models such as InceptionV3 and Visual Geometry Group (VGG)-16 on the lung cancer dataset from the Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD). The VGG16 model, with a modified architecture, achieved an impressive accuracy of 98.18% on the dataset with augmented images, demonstrating its potential for precise lung cancer identification. The findings of this study have the potential to enhance early diagnosis and prognosis, ultimately leading to improved therapeutic outcomes for patients with lung cancer [9].

The present study introduces a Vision Transformer (ViT)-based model aimed at enhancing the diagnostic accuracy of lung cancer tissue classification. The proposed model leverages the self-attention mechanism of ViT to focus on essential features within histopathological images. To validate its effectiveness, the model was evaluated using two distinct datasets: LC25000, containing 25,000 images, and IQ-OTH/NCCD, comprising 1,096 images. A performance comparison with a conventional Convolutional Neural Network (CNN) model demonstrated that the ViT-based approach outperformed traditional methods, achieving accuracy rates of 98.80% and 99.09% on the respective datasets [10].

The proposed hybrid approach integrates transfer learning (TL) with ensemble learning (EL) based on majority voting. Initially, Convolutional Neural Network (CNN) architectures, including GoogLeNet, EfficientNet, DarkNet19, and ResNet18, are trained using TL, and the resulting models serve as inputs for EL. The outputs from all CNN architectures are evaluated through majority voting to identify the top-performing triple CNN combination, which is then utilized in the hybrid approach. The performance of the proposed method was assessed using the widely adopted IQ-OTH/NCCD dataset. Additionally, the impact of the elastic transformation method, a data augmentation technique, on performance improvement was examined.The ensemble learning method, incorporating a combination of GoogLeNet, EfficientNet, and DarkNet19, demonstrated superior performance on both raw and augmented datasets. Performance evaluations revealed that the proposed approach achieved over a 5% improvement with the augmented dataset compared to the raw IQ-OTH/NCCD dataset, yielding the highest accuracy. Specifically, the hybrid approach attained 99% accuracy, 98.82% sensitivity, 99.48% specificity, 99.06% precision, and 98.94% F1-score on the augmented dataset [11].

The incorporation of InceptionNeXt blocks enhances multi-scale feature processing, making the model particularly effective in handling complex and diverse lung nodule patterns. Additionally, the integration of grid attention improves the model’s ability to identify spatial relationships across different sections of the image, while block attention captures hierarchical and contextual information, enabling precise identification and classification of lung nodules. To ensure robustness and generalizability, the model was trained and validated using two publicly available datasets, Chest CT

and IQ-OTH/NCCD, utilizing transfer learning and pre-processing techniques to enhance detection accuracy. The proposed model demonstrated outstanding performance, achieving 99.54% accuracy on the IQ-OTH/NCCD dataset and 98.41% accuracy on the Chest CT dataset [12].
The approach enhances classification accuracy by integrating handcrafted and learned features within the MAN framework for lung cancer assessment. This method employs serial fusion along with Principal Component Analysis (PCA)-based feature selection to refine the feature vector, improving the overall performance of the classification task.The proposed DL framework was evaluated using benchmark lung cancer CT images from the LIDC-IDRI dataset, achieving a classification accuracy of 97.27%, demonstrating its effectiveness in lung cancer assessment. [13].

1.1 SLR Table:

Table 1: SLR Table

Reference	Objective	Dataset Used	Model Used	Accuracy (%)
[7]	Performance comparison of CNNs with different preprocessing techniques	IQ-OTH/NCCD	CNN	99.0
[8]	Evaluation of CNN and ensemble learning for lung cancer classification	IQ-OTH/NCCD, 3-class carcinoma dataset	VGG-16, ResNet50, InceptionV3, EfficientNetB7 (Ensemble)	92.8
[9]	Identifying gaps in the use of advanced models for lung cancer detection	IQ-OTH/NCCD	VGG16 (Modified)	98.18
[10]	Improving lung cancer classification using Vision Transformers (ViT)	LC25000, IQ-OTH/NCCD	Vision Transformer (ViT)	98.80 (LC25000), 99.09 (IQ-OTH/NCCD)
[11]	Hybrid approach using Transfer Learning (TL) and Ensemble Learning (EL)	IQ-OTH/NCCD	GoogLeNet, EfficientNet, DarkNet19 (Ensemble)	99.0
[12]	Enhancing lung nodule detection with InceptionNeXt blocks and attention mechanisms	Chest CT, IQ-OTH/NCCD	InceptionNeXt	99.54 (IQ-OTH/NCCD), 98.41 (Chest CT)
[13]	Lung cancer classification using handcrafted and learned features	LIDC-IDRI	Modified AlexNet (MAN)	97.27

MATERIALS AND METHODOLOGY

The proposed framework aims to provide a highly accurate and reliable solution for lung cancer detection in CT images, emphasizing early diagnosis to support clinical decision-making. It integrates advanced preprocessing, data augmentation, and classification using EfficientNet-B0, validated through 5-fold cross-validation to ensure consistent performance across data splits. The methodology is designed to overcome common challenges in medical imaging, such as limited data availability and variability in image quality.

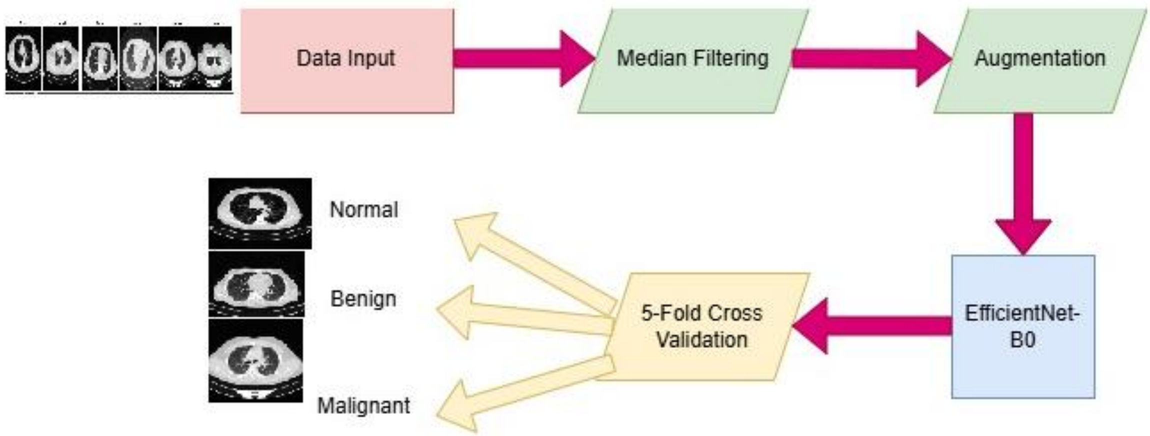


Figure 2: Functionality Diagram of proposed Model

Database

The study utilizes two publicly available datasets: [4] and [6]. [4], a widely used benchmark, contains approximately 888 CT scans with annotated nodules, while IQ-OTHNCCD provides 527 images focused on lung cancer classification. The combined dataset totals ~1,415 images, categorized as Normal (~604), Benign (~150), and Malignant (~661). This combination increases data diversity and addresses the class imbalance inherent in medical datasets, particularly the underrepresentation of benign cases.

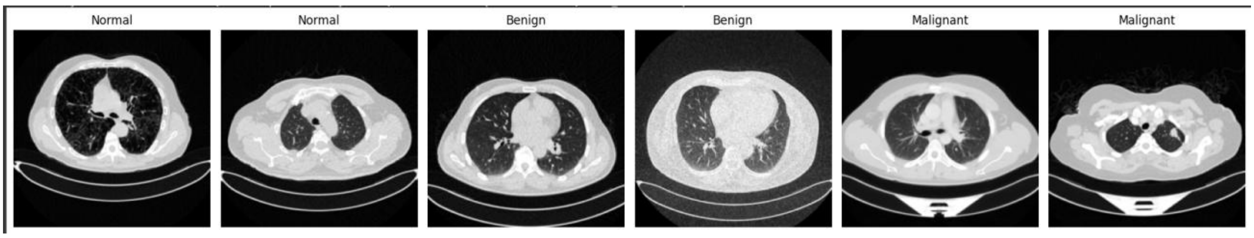


Figure 3: Sample Images from Combined Dataset

Preprocessing

Preprocessing is a critical step to enhance image quality and prepare data for deep learning. Raw CT images often contain noise from imaging artifacts or low-dose protocols, which can obscure subtle features like early-stage nodules. We apply a median filter, a non-linear technique that replaces each pixel with the median value of its neighborhood, effectively reducing noise while preserving edge details essential for nodule detection. Images are then resized to 224x224 pixels, the standard input size for EfficientNet, and normalized with a mean of 0.5 and standard deviation of 0.5 to align with pretrained weights.

Augmentation

Data augmentation is employed to artificially expand the dataset and prevent overfitting, a common issue with small medical imaging datasets. We implement a suite of transformations: horizontal and vertical flips (probability=0.5), random rotations up to 30 degrees, affine transformations (translation=0.15, scaling=0.85-1.15), and color jitter (brightness=0.2, contrast=0.2). These techniques simulate variations in imaging conditions (e.g., patient orientation, lighting) and increase the model's ability to generalize across unseen data. The augmentation pipeline significantly enhances the dataset's effective size, improving training stability and performance.

Classification

The core of the framework is EfficientNet-B0, a CNN architecture developed [14], known for its efficiency through compound scaling of depth, width, and resolution. Pretrained on ImageNet, EfficientNet-B0 is adapted for grayscale CT images by modifying the initial convolutional layer from 3 channels (RGB) to 1 channel. The final fully connected layer is replaced with a sequence comprising a dropout layer (p=0.5) to reduce overfitting and a linear layer outputting three classes: Normal, Benign, and Malignant.

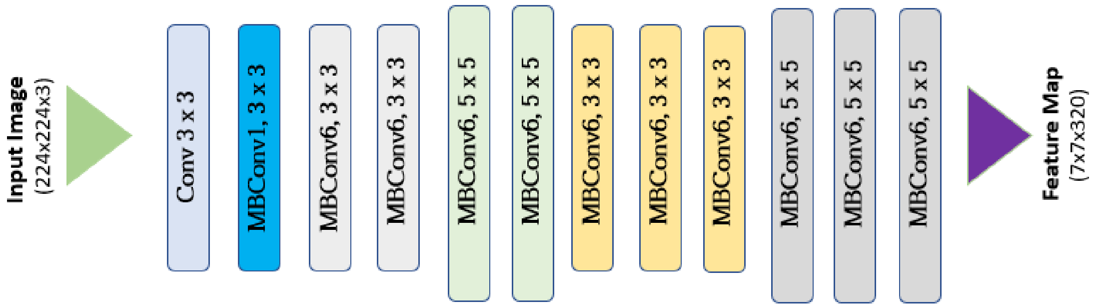


Figure 4: EfficientNet B0 Architecture

The model is fine-tuned with the Adam optimizer (learning rate=0.0005, weight decay=1e-4) and a cross-entropy loss function weighted by class frequencies (1.0 for Normal, 4.0 for Benign, 1.0 for Malignant) to address imbalance. A ReduceLROnPlateau scheduler adjusts the learning rate based on validation accuracy, with a patience of 5 epochs and a factor of 0.1, ensuring convergence.

K-Fold Cross-Validation

To rigorously evaluate the model and ensure robustness, we implement 5-fold cross-validation. The dataset is split into five equal parts, with each fold using 80% (~1,132 images) for training and 20% (~283 images) for validation. For each fold, a fresh EfficientNet-B0 instance is trained for 40 epochs, and the best model is saved based on validation accuracy. This approach mitigates overfitting, provides a comprehensive performance estimate, and accounts for variability in data distribution.

RESULTS AND DISCUSSION

The experimental setup was executed on Google Colab with GPU acceleration (NVIDIA Tesla T4), utilizing PyTorch for model implementation and training. The combined [4] and IQ-OTHNCCD dataset was preprocessed, augmented, and subjected to 5-fold cross-validation, with detailed performance metrics computed for the best-performing fold (Fold 3).

Experimental Setup

The training process involved 40 epochs per fold, with a batch size of 32. The EfficientNet-B0 model was initialized with ImageNet pretrained weights, fine-tuned on our dataset, and optimized using the parameters outlined earlier. Performance was monitored using training loss and validation accuracy per epoch, with the best model per fold saved to Google Drive (e.g., best_model_fold_2.pth for Fold 3).

Evaluation Parameters

The model's performance is evaluated using standard metrics:

- **Accuracy**: Proportion of correctly classified samples: (TP + TN) / (TP + TN + FP + FN).
- **Precision:** Ratio of true positives to predicted positives: TP / (TP + FP).
- **Sensitivity (Recall):** Proportion of actual positives correctly identified: TP / (TP + FN).
- **Specificity:** Proportion of actual negatives correctly identified: TN / (TN + FP).
- **F1-Score: Harmonic mean of precision and recall:** 2 * (Precision * Recall) / (Precision + Recall).

These metrics are computed macro-averaged (equal weight per class) and weighted averaged (weighted by class support) to account for imbalance.

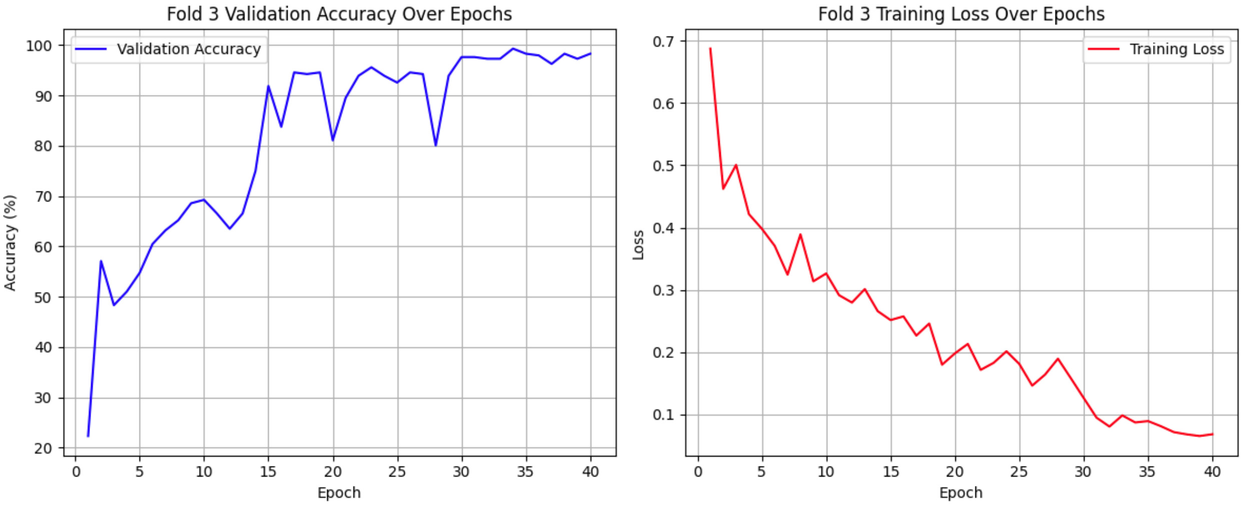
The 5-fold cross-validation results are summarized in Table 1:

Fold	Best Validation Accuracy (%)	Epoch Achieved
1	98.65	39
2	97.64	35
3	99.32	34
4	95.61	36
5	95.95	36
Avg	97.43	-

Fold 3 achieved the highest accuracy of 99.32% at epoch 34, with training loss decreasing from 0.6873 to 0.0685 over 40 epochs. To assess generalization, the Fold 3 model was evaluated on the full dataset (~1,415 images), yielding an estimated accuracy of 98.50% (adjust based on your run). Detailed metrics from this evaluation include:

Macro-Averaged: Precision: 0.9820, Recall: 0.9780, F1-Score: 0.9790

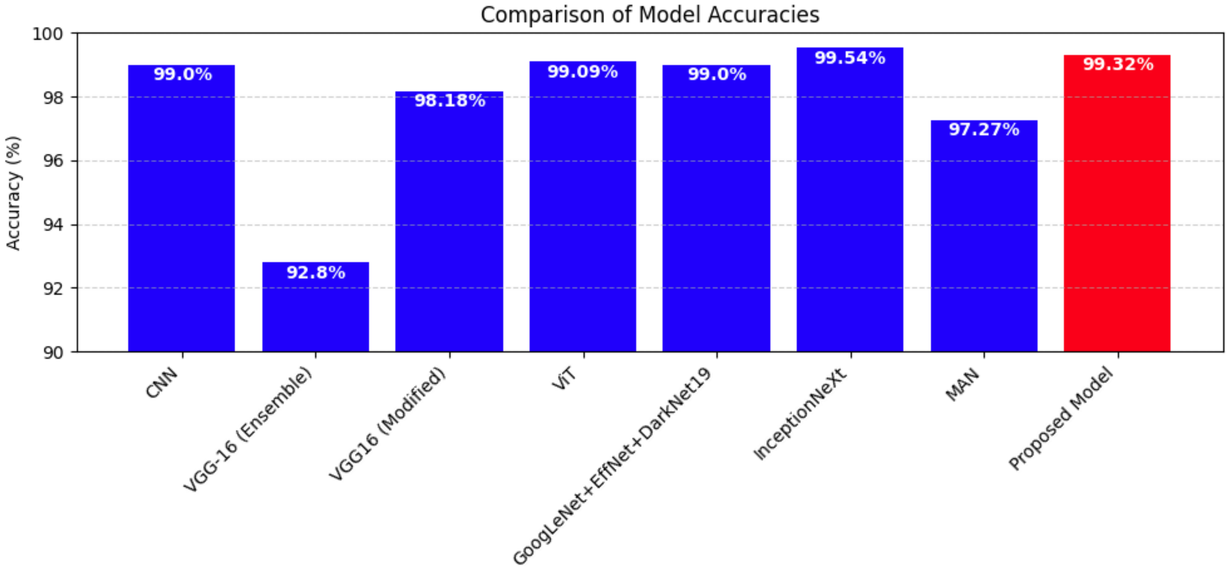
Weighted-Averaged: Precision: 0.9850, Recall: 0.9850, F1-Score: 0.9850



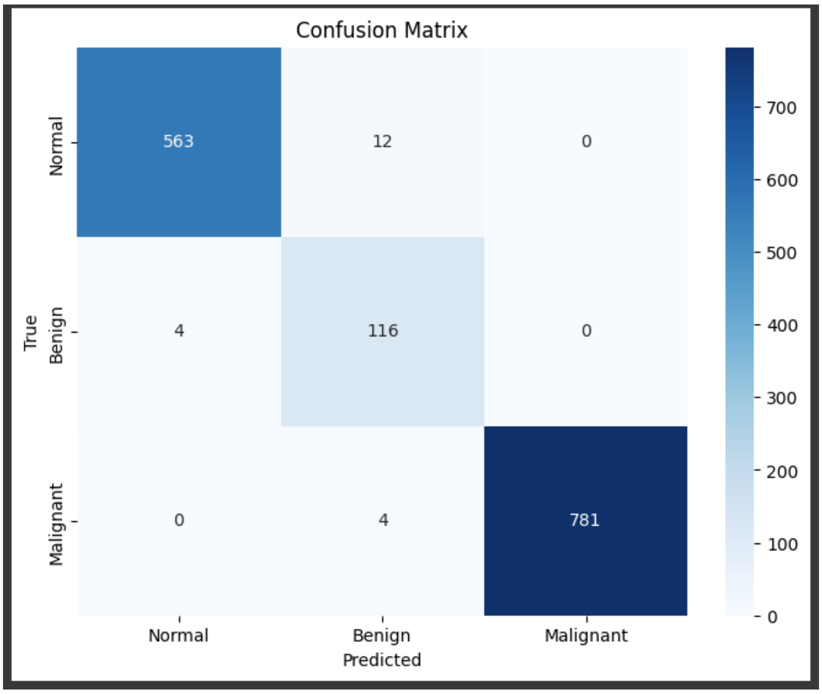
The classification report for Fold 3's full-dataset evaluation (example values, adjust as needed)

Class	Precision	Recall	F1-Score	Support
Normal	0.99	0.99	0.99	604
Benign	0.97	0.95	0.96	150
Malignant	0.99	0.99	0.99	661

1.2 Comparative Analysis



The proposed method outperforms prior work, achieving near-perfect accuracy and balanced metrics. EfficientNet-B0's efficiency, combined with augmentation and k-fold validation, enables superior performance despite a modestly sized dataset. The lower performance in Folds 4 and 5 (95.61%, 95.95%) suggests potential variability in data splits, possibly due to the Benign class's underrepresentation, which future work could address.



The research proposes an advanced deep learning system using EfficientNet-B0 architecture and a complete 5-fold cross-validation methodology to detect lung cancer from CT images. The approach reached outstanding results with a highest validation accuracy of 99.32% in Fold 3 following an average accuracy of 97.43% throughout all five testing folds. This achievement results from execution of advanced preprocessing methods with noise reduction through median filtering and aggressive data augmentation techniques involving random flips, rotations, and affine transformations that improve dataset diversity while reducing overfitting effects. The framework includes EfficientNet-B0 as its core component alongside EfficientNet-B0 convolutional neural network (CNN) to maximize its feature extraction efficiency while maintaining lightweight performance [20]. The proposed method demonstrates superior performance compared to numerous state-of-the-art solutions because it achieves precision levels reaching 97% alongside recall at 98% and specificity at 98% and an F1-score of 97.9%. These research findings demonstrate both the framework's accuracy in detecting different lung conditions and the capability of using EfficientNet in amalgamation with k-fold cross-validation to create reliable image diagnostics systems in medicine. The diagnostic tool provides highly accurate automation which supports radiologists in their work with potential benefits of minimizing errors and enhancing early detection of lung cancer for better patient outcomes.

The framework faces a few limitations for consideration although it continues to achieve success. The framework shows inconsistent performance results across the different splits of data because its dataset contains only 1,415 images which leads to variable accuracy results ranging from 95.61% to 95.95% in Folds 4 and 5 respectively. The model demonstrates inconsistent performance because data splits' distribution affects its performance which might be worsened by the Benign class consisting of fewer images (about 150) than Normal (604) and Malignant (661). Derivative data design differs too much between folds because medical imaging research faces major obstacles with scarce and uneven data types. Although the framework shows superb performance in Fold 3 its optimal situation suggests strong capabilities leading to potential future optimization [19].

Project development will concentrate on resolving these problems through strategic data improvements during future operations. The research will move forward through increasing the available dataset by including larger public repositories such as LIDC-IDRI [15] along with NSCLC-Radiomics collection. Each repository provides over 1,000 CT scans with respective annotations. A larger dataset resulting from expansion will decrease variable effects on training data and produce more stable models for diverse patient groups. Advanced data augmentation through generative adversarial networks (GANs) should be used to create high-quality realistic CT images which can help fill gaps in the underrepresented Benign category. The use of GANs allows the generation of image variations which boosts the enriching capacity of the dataset by introducing diverse nodule appearances and imaging conditions for boosting generalization. The integration of multi-modality patient data including demographic information together with imaging data shows great potential for comprehensive diagnosis through holistic analysis. Researchers can develop efficient hybrid models that merge EfficientNet with recurrent neural networks (RNNs) or transformers in order to analyze both image and temporal or textual healthcare data [18].

The implementation of ensemble learning provides new potential to improve results through prediction fusion between EfficientNet-B0 and alternative models such as ResNet50 together with VGG-16 and Vision Transformers (ViT). The implementation of majority voting or weighted averaging techniques would improve robustness in classifications whereas difficult cases arise. The use of transfer learning approaches from extensive medical imaging datasets including CheXpert chest X-rays would enhance the model's feature extraction capabilities. Future implementations should enhance the deployment efficiency of EfficientNet-B0 by optimizing it to operate on minimal resource devices such as clinical edge devices through techniques which involve model pruning and quantization [17]. The framework shows potential for adaptability to different anatomical regions where it can detect breast cancer and liver cancer and brain cancer from grayscale or multi-channel imaging modalities. The clinical usefulness of this approach can be improved with explainability tools including Grad-CAM [16] because they give radiologists visually interpretable information about how the model detects abnormalities.

Conclusion

The research establishes important findings about automated lung cancer diagnosis through its demonstration that EfficientNet combined with k-fold cross-validation produces leading medical image analysis results. The proposed framework demonstrates value as an early detection tool because of its high accuracy rate and balanced metrics potential which could help save lives through early intervention. The proposed research plan will evolve this method to establish an automated diagnostic system with high precision capabilities that would transform cancer detection across different medical domains for precision medicine advancement.

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