

Early detection of lung cancer through CT scan images using MobileNetV2

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Abstract: Early detection of lung cancer stands essential because it represents one of the leading causes of global cancer- connected fatalities. The research establishes a classification system using MobileNetV2 deep learning methodology to sort lung CT scan images among three diagnostic categories of normal and benign and malignant types, this version of MobileNetV2 proved suitable for processing CT lung images through the adaptation of the network using the IQ-OTH/NCCD dataset. Through a transfer learning approach, the model attains accurate results in classification tasks while decreasing both training operations and infrastructure requirements because it successfully extracts intricate features. The model demonstrates remarkable performance by achieving an average accuracy of 91% which shows its capability to assist medical diagnosis while helping with large-scale lung cancer screening even in environments that lack substantial computational power.

Keywords: Lung cancer, MobileNetV2, deep learning, image preprocessing.

Introduction

Despite major progress in the field of medical science, lung cancer continues to be a leading cause of cancer mortality across the globe, an indication of the importance of early diagnosis in enhancing survival prospects. Lung cancer is defined by the uncontrolled proliferation of neoplastic cells within the pulmonary tissues. Among the various causative factors, tobacco consumption is the most prominent, responsible for about 85 Percent of all lung cancer cases. Early diagnosis significantly enhances the likelihood of effective treatment; however, traditional diagnostic methods like CT scans are highly prone to human bias, that proneness can lead to delayed diagnosis, particularly in early malignancies, because of observer variation and low sensitivity [1] Deep learning (DL) and machine learning (ML) have emerged as strong tools for medical imaging over the past few years, offering improved accuracy, speed, and reliability in classifying and detecting lung cancer. These techniques have shown special utility in distinguishing between benign and malignant lesions, the detection of fine patterns in CT scans, and the prediction of disease progression, especially in populations at high risk like chronic smokers. [2] [3] Moreover, lightweight CNN architectures and transfer learning have also improved the diagnostic performance while lowering computational complexity [4] This paper addresses the use of machine learning techniques for early lung cancer detection, especially in those at high risk due to tobacco consumption. It reviews a number of supervised and deep learning approaches and analyzes their performance according to well-established measures such as accuracy, sensitivity, and specificity. The study also includes insights from newer literature to highlight the growing importance of artificial intelligence-based systems in enhancing diagnostic accuracy and individualizing patient outcomes.

Related work

Lung cancer is the second most common cancer worldwide and the leading cause of cancer-related deaths. There are several factors as to why it may occur but the primary cause is smoking. Although, it also happens to individuals who live in polluted environments, are exposed to passive smoking or due to other genetic factors. Tabreer T. Al-Shouka et al. [4] investigated the application of transfer learning-based CNNs to detect lung cancer from CT scans with high accuracy. They employed pre-trained models—ResNet, MobileNetV2, Xception, and VGG16—and ResNet was found to perform best with 94 percent accuracy and 0.16 testing loss. The study enumerates the advantages of transfer learning as minimized training time, avoidance of overfitting, and computational efficiency and suggests enormous potential in clinical diagnostics and the need for more evidence.

Aman Bhatt et al. [1] presented a deep learning pipeline for early detection of lung cancer from CT scan images. With the IQ-OTH/NCCD dataset of 1,190 labeled scans, the authors employed rigorous preprocessing—resizing, normalization, and augmentation—to optimize performance. Their CNN model had a 99 percent validation accuracy and F1-score, showing excellent classification capability. The research highlights the clinical promise of AI-driven diagnostic tools to enhance accuracy and reduce delays and invites further work to ensure safe integration into healthcare settings.

Bakchy et al. [2] proposed a lightweight CNN model to classify three lung cancer types from 15,000 CT scan images. The model obtained 99.48 percent validation accuracy and an ideal AUC of 100 percent, with extremely high precision, recall, and F1-score. It requires less computer power with fewer parameters. Grad-CAM was also utilized in the study to generate heatmaps for better comprehension. This paper demonstrates how lightweight models can yield accurate, comprehensible, and efficient diagnostic tools for lung cancer.

Begum et al. [3] suggested a light-weight deep learning model for the early detection of lung cancer, combining clustering techniques with an image analysis algorithm using CNN. Preprocessing was applied to CT scan images to detect the nodule region of interest, and SMOTE was applied to balance class distribution. Their 2D-CNN, made up of convolutional, ReLU, pooling, and dense layers, achieved 97 percent accuracy and 96 percent precision. The research confirms the effectiveness of automated diagnostic tools in enhancing detection accuracy, supporting clinicians, and allowing timely, cost-effective treatment.

Ozdemir et al. [5] suggested a hybrid deep model architecture combining Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) for the detection of lung cancer from CT imaging. The model uses InceptionNeXt blocks with grid and block attention mechanisms to efficiently extract local and global features. It obtained 99.54 percent and 98.41 percent accuracy rates on the Chest CT and IQ-OTH/NCCD datasets, respectively, under a lightweight setting of 18.1 million parameters. The approach outperformed other models, which indicates its potential to enhance diagnostic accuracy and guide clinical decision-making processes.

Chen et al. [6] built a strong transformer-based deep learning approach to predict lung cancer risk based on Taiwan's vast health database of 23 million people with electronic claims records (ECRs). The model utilized an well-designed cohort selection with a predictive performance of over 2.1, with AUCs of 0.668 (all-stage) and 0.645 (early-stage). Through the identification of high-risk persons in an efficient manner,

this method provides an extensible method of early intervention, with the aim of streamlining screenings and eventually minimizing lung cancer-related deaths.

Methodology

The various stages of the proposed detection system have been discussed in detail in the following:

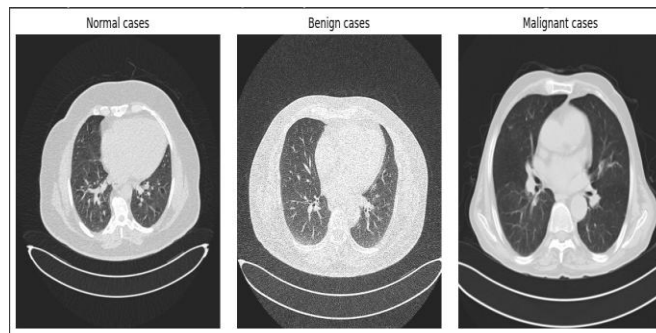


Fig. 1. Sample images from each class (Normal, Benign, Malignant) of the IQ-OTHNCCD dataset

A. Dataset

The dataset that has been used in this paper contains high resolution 3D CT scan images, consisting of 3 classes namely- Benign cases, Malignant cases and Normal Cases. This dataset contains a total of 1098 images where 120 images belong to Benign cases, 561 files belong to Malignant cases and 416 files belong to Normal cases. The collection of this dataset took place in Iraq in fall of 2019 over a course of three months. [7]

B. Preprocessing

The following preprocessing has been done before training the model.

- **Image resizing:** The images of the dataset have been resized to 224 x 224 pixels to fit the input size of the model MobileNetV2. This resizing is done to ensure consistency across the convolutional layers of the model.
- **Colour channel adjustment:** Since the dataset that has been used has grayscale CT scan images but MobileNetV2 has been trained on ImageNet so it expects RGB format. So, grayscale images were converted to RGB images across all channels.
- **Normalization:** To improve training stability and performance, all image pixel values were normalized to the range [0, 1] by dividing each pixel value by 255. This normalization helps the model converge faster during training and prevents large gradient values.
- **Data augmentation:** This is done on training set only. Due to the limited size of the dataset, the training set has undergone various techniques like rotation by (+- 20 degree), translation by (+20%) along both height and width, horizontal flipping and brightness adjustment. This is done to prevent overfitting. Feature wise normalisation has also been applied to make the training more stable.
- **Label Encoding:** One hot encoding was used to convert the labels, that is, the three classes of the model, malignant, benign and normal to a machine-readable format.

C. Proposed model

MobileNetV2 is a lightweight, low computational convolutional neural network architecture that was designed by google in 2018. It was specifically designed for efficient neural networks which perform well on mobile devices. The key features of this model are that, firstly, it uses inverted residuals, which implies that these blocks expand then apply depthwise convolution and then project back to a smaller space which keep the computations low while preserving the representational power. Secondly, the model uses Linear bottlenecks. This was done to prevent the loss of information by avoiding non-linear activation at the bottleneck layers. [8]

D. Experimentation details

The proposed model was implemented using Tensorflow library and Keras api. The training was executed on NVIDIA Tesla T4 via Google Colab. The training was done over 20 epochs and the batch size used was 16 with a learning rate of 0.0001 respectively For optimization of the model weights, AdamW optimizer was used with Categorical Cross entropy Loss. Early stopping was also included as a callback during training to prevent overfitting by monitoring the validation loss. A patience of 5 epochs was set.

Results

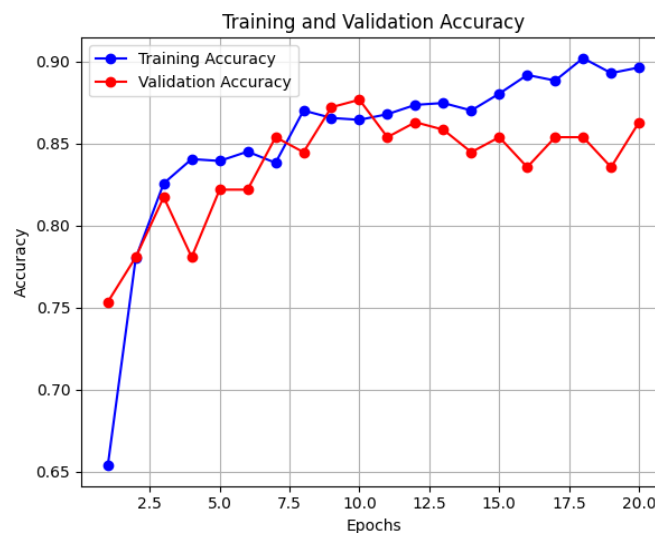


Fig. 2. Training and Validation accuracy

TABLE I
Performance Metrics of the Model Across All Classes

Metric	Benign	Malignant	Normal	Mean
Accuracy	—	—	—	91
Precision	41	95	80	72
Recall	29	100	81	70
F1-Score	34	97	80	70
Specificity	94	94	89	92

The proposed model has been evaluated using key metrics such as accuracy, precision, recall and F1-score. Fig2 shows the graphs of training and validation accuracy.

Table 1 shows the summarised results of the model. The model achieved a high overall accuracy of 91% with particularly strong performance in detecting malignant cases, reflected by a precision of 0.95, recall of 1.00, and F1-score of 0.97. These results indicate that the model is highly sensitive to malignant tumors, which is crucial for early detection and timely treatment. For the Normal class, the model achieved an F1- of 0.80, demonstrating reliable performance. However, the performance on the Benign class was relatively lower, with a precision of 0.41 and recall of 0.29, likely due to class imbalance. The mean F1-score across all classes was 0.70, and the mean specificity was 0.92, suggesting the model's overall ability to correctly identify negative cases and minimize false positives. Table 2 shows the comparison between the existing methods on Lung Cancer disease detection from CT scan images with the method proposed in this work. It is clear from this table that the proposed MobileNetV2 model shows a performance superior to the existing state-of-the-art methods.

Conclusions

In this research, stages of Lung cancer have been classified from CT scan images using a lightweight model called MobileNetV2. For the proposed work, the authors CT scans from the IQ-OTHNCCD dataset. The proposed model's performance has been evaluated on major metrics like Accuracy, Specificity, Sensitivity and F1-Score. The proposed mixer model is able to achieve a mean accuracy, precision, recall, F1-score, specificity of 91%, 72%, 70%, 70% and 92% respectively. The evaluation results show that the model achieves great performance compared to recent methods proposed in various literature.

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