Lung Cancer Classification from Chest CT Scans using EfficientNet

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ABSTRACT
Lung cancer is the leading cause of cancer-related deaths, and early detection is critical for improving survival. This study presents an explainable deep learning approach for classifying chest CT scans into normal, benign, and malignant categories. Six pretrained convolutional neural networks were evaluated on the public IQ-OTH/NCCD dataset using class-weighted training and light data augmentation. EfficientNet-B0 achieved the best performance, with 99.39% accuracy, a 0.988 macro F1-score, and 0.996 AUC, while correctly identifying all malignant cases.

Keywords
Lung cancer, Computed tomography, Transfer learning, EfficientNet, Grad-CAM, Explainable AI, Deep learning, IQ-OTH/NCCD

1. INTRODUCTION
Lung cancer is the leading cause of cancer death worldwide and is among the most diagnosed cancers [1], [2]. Most cases are found late, when treatment helps less and survival is poor [3]. Found early, while a nodule is still small and local, the odds improve sharply, which is why low dose computed tomography screening has become central to lung cancer care. A single scan holds many slices, and a screening service produces thousands of scans, so reading them by eye is slow and the results vary between readers. Computer aided tools that flag suspicious slices help with both speed and consistency [4].

Convolutional neural networks have driven most of the recent progress in medical image analysis [5] and have reached expert level on tasks such as skin lesion grading and chest X-ray reading [6]. Training such a network from scratch needs a large, labelled set, which is hard to gather in a clinic. Transfer learning avoids this by reusing a network trained on a large general collection such as ImageNet [8] and tuning it on the smaller medical set. Accuracy alone is still not enough for clinical use. A model that only returns a label is hard to trust, so visual explanation methods such as Grad-CAM, which draw a heat map over the regions that drove a prediction [9], are now seen as a basic need for medical AI [10].

In this paper we build a transfer learning pipeline for three class lung cancer classification on chest CT and give equal weight to accuracy and explanation. Our main contributions are as follows.

a) We fine tune six ImageNet pretrained networks under one shared protocol on the IQ-OTH/NCCD CT dataset and report a fair side by side comparison.
b) We handle the strong class imbalance, where benign cases are rare, with class weighted training and light augmentation, and we report per class scores rather than accuracy alone.
c) We identify EfficientNet-B0 as the strongest and most efficient model, reaching 99.39 percent accuracy with only about four million parameters.
d) We add Grad-CAM heat maps that show the model attends to the lung region, which supports clinical trust, and we place our results next to recent work on the same dataset.

2. RELATED WORKS
Deep learning for lung cancer on CT has grown quickly, and several reviews survey the field [11], [12], [13]. Early work focused on lung nodules, which were classified with deep residual networks and migration learning [14] and later scored more accurately with ensemble voting over ResNet features [15], attention blocks on a ResNet backbone [16], and hybrid models that stack several pretrained networks [17]. The IQ-OTH/NCCD dataset has become a common benchmark. It was introduced with an AlexNet style network [18] that reached about 93.5% accuracy [19], and the same group also tried a support vector machine [20] and a GoogLeNet transfer learning setup [21]. Recent studies push accuracy near or above 99 percent using a network tuned by the Ebola optimization search algorithm [22], a LeNet study [23], a VGG16 feature extractor with an extremely randomized selector [24], an EfficientNet variant called Lung-EffNet [25], a sine cosine tuned network [26], a double layer CNN with heavy preprocessing [27], and a CNN ensemble combined through a Mitscherlich function [28]. Early detection of cancer has a great impact on increasing patient survival, on reducing treatment intensity and on lowering healthcare costs in the long term. Despite advancements in genomics, imaging, biomarkers and EHR analytics, it's difficult for current tools, due to the various sources of data. This makes it difficult to detect cancers when patients have few, if any, symptoms. To address this issue, [39] propose a Multimodal Data Analytics Framework (MDAF).

Many of these report strong accuracy but rely on complex pipelines, large models, or extra optimization stages, and few report how the rare benign class is handled or show any visual explanation. Explanation methods have a parallel history. Class activation mapping localized the object that drives a decision [29], and Grad-CAM generalized this to almost any CNN through gradient weighting [9], a technique now widely used to audit medical models [10]. Class imbalance is another common problem, often treated with weighted loss and resampling [30]. The same learning methods serve related clinical tasks, from lung cancer biomarker discovery [31] to breast cancer classification [32] and dementia detection [33]. [38] proposes Smart-LungNet, an automated deep learning framework designed to classify lung conditions into three categories: Normal, Lung Opacity, and Viral Pneumonia. Utilizing the Lung X-Ray Image Dataset of 3,475 images. Smart-LungNet achieves a testing accuracy of 89.85% and an F1-score of 89.84%, outperforming ResNet18, DenseNet 121 and MobileNetV2 [38].

Our work brings these threads together. We keep the model simple and light, we report per class behaviour on an imbalanced three class task, and we attach Grad-CAM explanations to the final model.

3. DATASET ANALYSIS

We use the public IQ-OTH/NCCD lung cancer dataset, which was collected at the Iraq-Oncology Teaching Hospital and the National Center for Cancer Diseases [19], [34]. The labelled part holds 1097 axial CT slices from three groups. There are 416 normal slices, 120 benign slices, and 561 malignant slices. The images are stored as 512 by 512 grayscale pictures, with a small number saved at slightly different sizes.

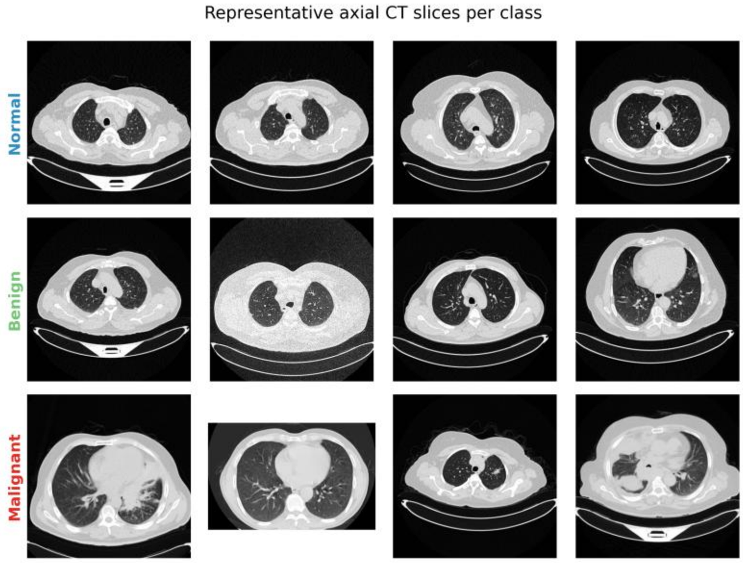

Fig 1 Axial CT slices for the three classes in the IQ-OTH/NCCD dataset.

Fig. 1 shows a few examples slices from each class. The visual differences between groups are subtle, which is what makes the task hard for the human eye and a good fit for a learned model. Fig. 2 shows the class counts. The set is clearly imbalanced. Malignant cases make up about 51 percent of the data, normal cases about 38%, and benign cases only about 11%. The small benign group is the main difficulty, because a model can score well on overall accuracy while still missing this class.

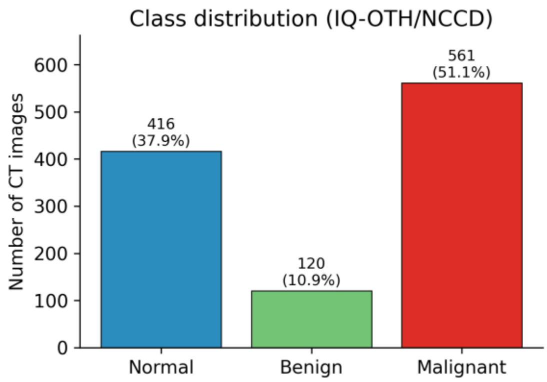

Fig 2 Class distribution of the labelled IQ-OTH/NCCD slices, showing the small benign group

We also looked at pixel intensity. The average intensity histograms of the three classes overlap heavily, with class means between 101 and 106 on a 0 to 255 scale. This overlap confirms that simple brightness-based rules will not separate the classes and that richer features learned by a network are needed. We split the data once into training, validation, and test parts using a 70, 15, and 15 percent ratio, with the split done inside each class so the rare benign group keeps its share in every part. This gives 768 training, 164 validation, and 165 test slices. The same split is reused for every model, so the comparison stays fair.

4. METHODOLOGY

4.1 Preprocessing and Augmentation

Each slice is resized to 224 by 224 pixels, which matches the input size of the ImageNet pretrained networks. The grayscale image is copied across three channels and normalized with the standard ImageNet mean and standard deviation. During training we apply light augmentation to reduce overfitting on the small set. This includes a random resized crop, a random horizontal flip, a small rotation up to ten degrees, and a mild change in brightness and contrast. The validation and test images are only resized and normalized, with no augmentation.

4.2 Transfer Learning Models

We study ResNet-18 [35], VGG-16 [36], and EfficientNet-B0 [37]. EfficientNet is a family of convolutional neural networks designed to achieve optimal accuracy while maintaining computational efficiency through compound scaling of network depth, width, and resolution [40]. Each one starts from weights learned on ImageNet [8]. We replaced the original classification head with a new linear layer that has three outputs, one per class, and we fine tune the whole network on the CT data. Fine tuning all layers, rather than freezing the backbone, let the early filters adapt to the texture of CT scans, which differs from natural photos.

4.3. Handling Imbalance and Training

To stop the model from ignoring the rare benign class, we weight the cross-entropy loss by the inverse of each class frequency, so an error on a benign slice costs more than an error on a common class. We also add a small amount of label smoothing to keep the model from becoming overconfident. Training uses the AdamW optimizer with a learning rate of 0.0001, a weight decay of 0.0001, and a batch size of 32. The learning rate follows a cosine schedule over 40 epochs. We train with mixed precision for speed and keep the model that scores the best macro F1 on the validation set, stopping early if it does not improve for ten epochs. All work runs on a single GPU.

4.4. Explainability and Evaluation

For the final model we generate Grad-CAM heat maps from the last convolutional block [9]. The method weights the feature maps by the gradient of the predicted class, then sums and rescales them to highlight the regions that support the decision. We report accuracy together with macro averaged precision, recall, and F1 score, since macro averaging treats the rare benign class on equal footing with the others. We also report the area under the ROC curve using a one versus rest scheme. Precision, recall, and F1 are given per class so the behaviour on benign cases is visible.

5. RESULTS AND DISCUSSION

Table 1 reports the test results for all six backbones under the shared protocol. Every model clears 96 percent accuracy, which confirms that transfer learning transfers well to this task. EfficientNet-B0 stands out. It reaches 99.39 percent accuracy, a macro F1 score of 0.988, and an area under the ROC curve of 0.996, while using only about four million parameters. It beats VGG-16, which holds more than 134 million parameters, on every metric.

Table 1 Test performance of the six fine-tuned backbones on IQ-OTH/NCCD. The best model is shown in bold.

Backbone	Acc.	Prec.	Rec.	F1	AUROC	Params (M)
EfficientNet-B0	0.994	0.995	0.981	0.988	0.996	4.0
ResNet-50	0.982	0.985	0.944	0.962	0.990	23.5
VGG-16	0.976	0.952	0.952	0.952	0.974	134.3

Because the benign class is small, the per class view matters more than the headline number. Table 2 gives the per class scores for EfficientNet-B0. The model reaches perfect precision and recall on malignant cases, which is the most important outcome in a screening tool, since a missed cancer is the costliest type of error. It also handles the rare benign class well, with a recall of 0.944. Figure 3 shows the confusion matrix and the ROC curves. Out of 165 test slices the model makes a single mistake, where one benign slice is read as normal. No malignant slice is missed, and the curves sit close to the top left corner for all three classes.

Table 2 Per class test scores for the proposed EfficientNet-B0 model.

Class	Precision	Recall	F1-score	Support
Normal	0.984	1.000	0.992	63
Benign	1.000	0.944	0.971	18
Malignant	1.000	1.000	1.000	84

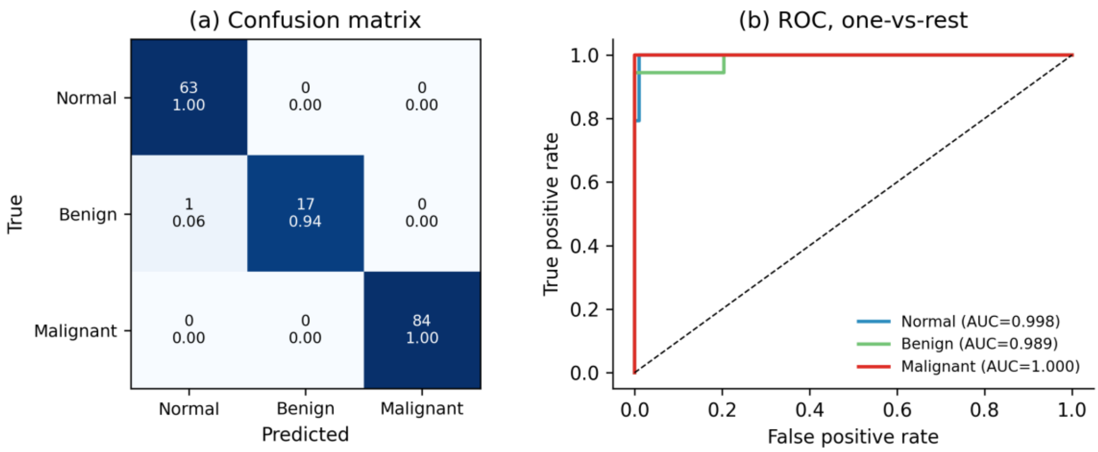

Fig 3 Test set results for EfficientNet-B0 model. (a) Confusion matrix. (b) ROC curve

Table 3 places our result next to recent studies that used the same IQ-OTH/NCCD dataset. The early dataset paper reported about 93.5 percent accuracy with an AlexNet style network [19], and a support vector machine on the same scans reached about 89.9 percent [20]. Recent deep models report figures from 99.0 to 99.6 percent [22], [24], [25], [26], [27], [28]. Our EfficientNet-B0 sits firmly in this top group at 99.39 percent. The point we want to stress is not that we set a new record, but that a single lightweight model, trained with a plain protocol and no extra optimization stage or ensemble, matches methods that are far more complex. It does so while also giving per class scores and visual explanations, which most of the compared studies do not provide.

Fig. 4 shows Grad-CAM heat maps for one correctly classified slice from each class. The warm regions fall over the lung fields and the area around the lesion, not on the body outline or the empty background. This tells us the model has learned to look where a radiologist would look, which builds confidence that the high accuracy comes from real image content and not from a shortcut in the data

Table 3 Comparison

Study	Year	Method	Accuracy (%)
Al-Yasriy et al. [19]	2020	AlexNet CNN	93.55
Kareem et al. [20]	2021	SVM	89.89
Al-Huseiny and Sajit [21]	2021	GoogLeNet (transfer learning)	94.38
Mohamed et al. [22]	2023	EOSA-CNN	93.21
Nitha and Vinod Chandra [24]	2023	VGG16 + ExtRanFS	99.09
Raza et al. [25]	2023	Lung-EffNet (EfficientNetB1)	99.10
Pathan et al. [26]	2024	SCA optimized CNN	99.00
Majumder et al. [28]	2024	MENet (CNN ensemble)	99.54
Musthafa et al. [27]	2024	Double layer CNN	99.64
This work	2024	EfficientNet-B0 (transfer learning)	99.39

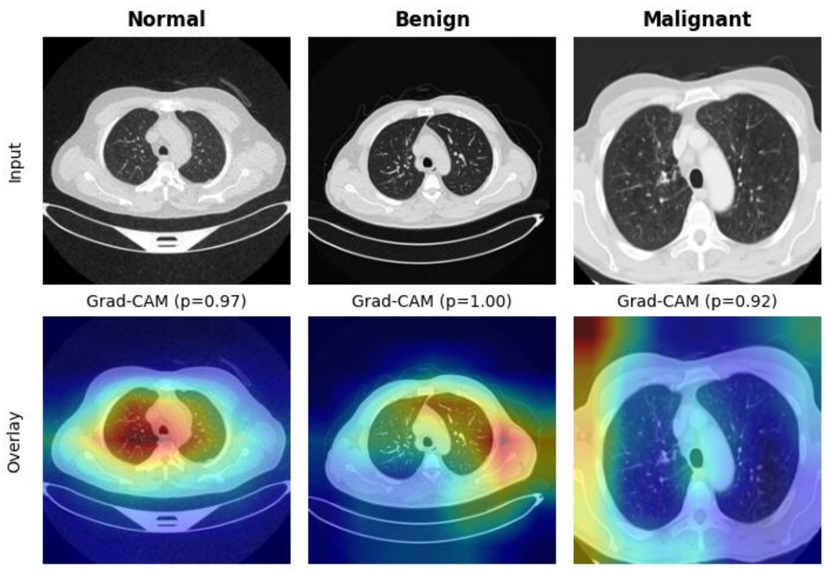

Fig 4 Grad-CAM heat maps for the proposed model on test slices from each class. Warm areas mark the regions that drive the prediction.

A few limits are worth stating plainly. We used a single stratified split rather than full cross validation, because the benign class is too small to divide into many folds without making each one unstable. The labels are given at the slice level, so we do not model the link between slices from one patient. The study also uses a single source dataset, and results on scans from other hospitals and scanners may differ. These points set the direction for future work, which includes patient level evaluation, testing across more than one dataset, and adding lesion segmentation to sharpen the explanations.

6. CONCLUSION

We presented an explainable transfer learning pipeline for three class lung cancer classification on chest CT. By fine tuning six ImageNet pretrained networks under one protocol and handling the class imbalance with weighted training, we found that EfficientNet-B0 gives the best balance of accuracy and size. It reached 99.39 percent accuracy with a macro F1 score of 0.988 and identified every malignant scan in the test set, all with a model of only about four million parameters. Grad-CAM heat maps confirmed that the model focuses on the lung region. The result shows that a simple, light, and transparent model can match heavier methods on this benchmark, which makes it a practical choice for computer aided lung cancer screening. Future work will test the approach on patient level data and on scans from several centres and will pair the classifier with segmentation for finer explanations.

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