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(RESEARCH ARTICLE)

EfficientNet-based deep learning framework for multiclass lung cancer classification using CT scan images

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Abstract

Lung cancer is extremely challenging to treat and detect. It is responsible for more deaths compared to other types of cancer globally. Due to the combination of complex diagnostic techniques and a lack of early detection, many patients only discover they have lung cancer in its late stages. This leads to even more difficulty and complexity in treatment. One of the most effective ways to treat lung cancer is to detect it early. When it first develops, lung cancer is very difficult to detect even with the use of specialized medical imaging. CT scans are the most effective and widely used imaging techniques for lung diagnostics. However, special trained personnel are required to analyze the results. This form of diagnosis is slow and is known to have high variability based on who the specialist is. Deep and machine learning research has made significant progress in the area of automated diagnosis imaging. This paper describes a deep learning approach to automating lung cancer diagnosis using CT imaging. The proposed method is based on EfficientNet and its ability to classify imaging data quickly and accurately. The method is shown to capture the nuances of lung imaging and provide a front-line service for diagnosis to support the clinical staff. The method is also scalable for multiple deployments.

Keywords: Detection of Lung Cancer; Deep Learning; CT Imaging; Transfer Learning; Computer-Aided Detection; Multiclass Classification; AI in Healthcare

1. Introduction

There has always been an alarming increase in the number of lung cancer patients globally. The WHO states that lung cancer is responsible for nearly 18% of the morbidities reported by the world's population. The leading cause of death due to lung cancer is attributed to late diagnosis. In the early stages of the disease, there are no noticeable symptoms, and by the time the disease has progressed to the late stage, the clinical symptoms are quite debilitating and treatment options become ineffective.

Detection of lung cancer in its early stages remains the most effective option. Studies have shown that the survival rates of patients diagnosed in Stage I or II of lung cancer are considerably higher as compared to those diagnosed in the later stage of the disease [2]. Hence, there is an increasing need for effective screening systems to facilitate early detection of lung cancer.

Currently, CT imaging is the most effective method of screening patients for lung cancer as it has the capability of highlighting most abnormalities in lungs and nodules, as reported in the literature [3]. CT imaging systems capture the highest resolution images of the lungs, and the radiologists have to manually review each CT slice to find nodule(s) or distortion(s). The biggest problem with manual diagnosis is that it is hugely subjective and has the potential to cause delays, and also significant variability in diagnosis. Small nodules can easily be missed during the review, leading to false negative reporting. Conversely, normal tissue can be misclassified as abnormal leading to positive reporting.

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AI is changing the future of medical imaging. With the introduction of deep learning and convolutional neural networks (CNNs) to the field, image classification is no longer a manual process. With CNNs, the images are processed, the features are extracted, and the classification is complete all in an automated pipeline [4]. Because of the incredible capabilities of CNNs, systems built with them have dominated the field of medical imaging over traditional machine learning systems which relied heavily on engineered features.

The adoption of deep learning to healthcare imaging has been made even easier with the advent of transfer learning. The use of transfer learning allows deep learning frameworks which have been built and trained for a certain task and have large training datasets to be modified slightly to work for the task of interest [5]. Coupling this approach with the scarcity of labeled medical imaging datasets, the training time of the framework for the task of interest will be reduced, and the framework's ability to generalize will be greatly increased.

Transfer learning has been used in the EfficientNet framework which is shown in Fig. 1 to perform tasks specific to the medical imaging field. The EfficientNet framework has had great success in lung medical imaging.

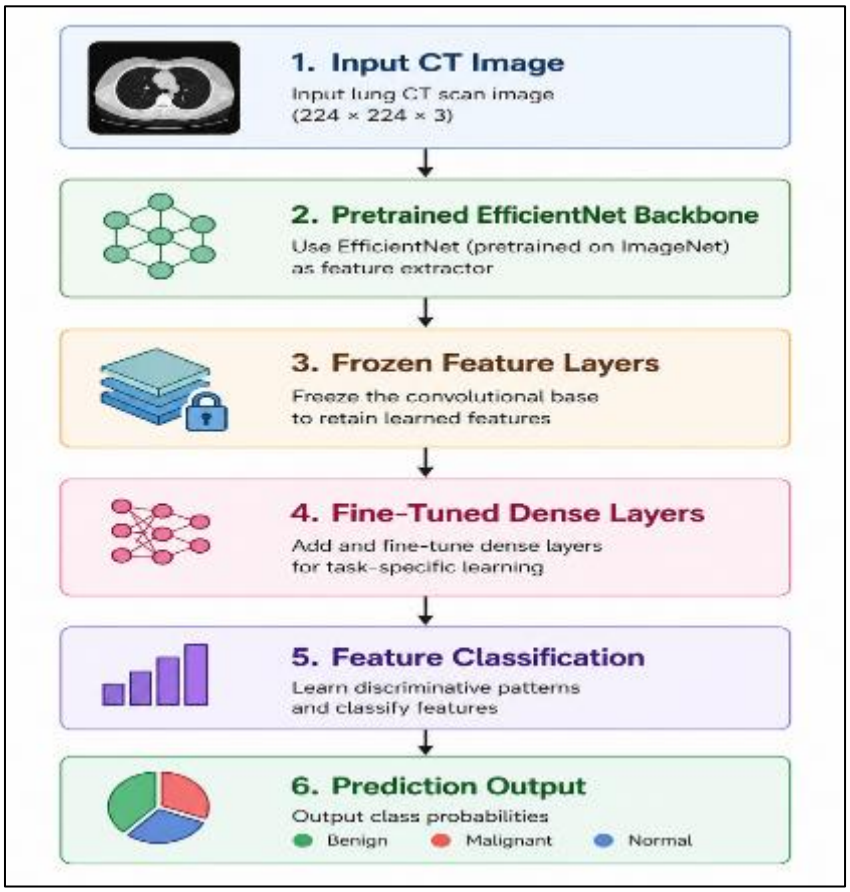

Figure 1 EfficientNet transfer learning architecture

Tan and Le built one of the more complex transfer learning architectures with EfficientNet [6]. The architecture is built around the process of compound scaling, optimizing the three axes of the architecture (depth, width, and resolution) to create a smaller architecture with less complexity which is still able to achieve better performance over classical architectures such as ResNet and DenseNet.

This research investigates using EfficientNet for transfer learning to perform classification on medical imaging CT scans of lungs to differentiate between normal, benign, and malignant lung conditions. The performance of the model on the given classification task is shown in the uploaded experimental results.

This research focuses on these key objectives:

- To construct a multiclass classification framework based on EfficientNet
- To assess classification accuracy based on experimental data provided
- To evaluate the performance of the confusion matrix for individual classes
- To assess the role of EfficientNet in computer-based-aided diagnosis

The results of the study justify the implementation of EfficientNet based AI in the clinical diagnosis of lung cancer to aid in fast and accurate diagnosis.

2. Review of Related Literature

The automation and reduction of human element errors in the diagnosis of lung cancer using AI based on deep learning techniques, sparked interest.

Low-dose CT scans were incorporated into a deep learning system for lung cancer detection with a reported performance level achieving that of a medical doctor. Volumetric deep learning improves the classification of pulmonary nodules. There also exist deep learning based CT scan systems that predict the prognosis of lung cancer, using CT scans, and provide predictive services. Despite the improvements these systems make to prediction, the quality and high computational demand of the services, limit their real-time performance.

The applicability of deep CNNs and architectures for the purposes of medical imaging, was made possible through the work of [Krizhevsky et al.]. The foundation was set by the early CNN architectures of deep learning for the purpose of medical imaging through the work of [Krizhevsky et al.](4). Yosinski et al. have provided a framework for the application of the concept of transfer learning to neural networks created for the purpose of a specific domain [5]. The work of [Tan et al. 6], EfficientNet achieved the best performance in CNNs with the least computing effort.

Li et al. used the EfficientNet model for medical image classification, and validated its generalization capabilities [9]. Wu et al. used EfficientNet to develop a series of lightweight medical diagnostic frameworks [10]. Saxena and Gupta developed hybrid CNN-SVM frameworks [11]. Liu et al. developed Attention-based CNN frameworks to focus on specific images and aid in localization [12]. Selvaraju et al. used Grad-CAM [13].

Even with these frameworks, problems still exist. These problems are:

- Dataset imbalance
- Overfitting on small medical datasets
- between normal and benign structures
- High computational cost
- Combining the transfer learning (TL) effectiveness and robust feature extraction capabilities of EfficientNet mitigates these limitations.

3. Methodology

This research aims to develop a classification framework for multi-class lung cancer within CT images based on deep learning and EfficientNet architecture . This framework will harness TL along with feature extraction, and will be aimed at maximization of classification performance with minimal training steps. This framework will be designed to engage in all steps of the process, from dataset preparation, to preprocessing images, to extraction of features, implementation of TL, construction of a classifier framework within the model, training of the model and evaluation of its performance.

3.1. Dataset Preparation

The dataset used in this study consists of CT scan lung images categorized into three distinct classes:

- **Benign Cases:** CT images containing non-cancerous pulmonary nodules.
- **Malignant Cases:** CT images containing cancerous nodules with visible abnormal growth patterns.
- **Normal Cases:** Healthy lung CT scans with no pathological abnormalities.

The collected dataset was divided into three subsets:

- **Training Dataset:** Used for model learning.
- **Validation Dataset:** Used for hyperparameter tuning.
- **Testing Dataset:** Used for final evaluation.

To ensure EfficientNet compatibility, all CT images were resized to: 224×224×3

Image resizing ensures consistent dimensionality for efficient feature extraction.

3.2. Image Preprocessing

Preprocessing is essential for improving image quality and enhancing model generalization.

Normalization

Pixel normalization was performed using:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

where:
X represents original image pixel values
μ denotes mean pixel intensity
σ denotes standard deviation

Normalization ensures stable gradient updates and accelerates convergence.

3.3. Data Augmentation

To increase training diversity and reduce overfitting, augmentation techniques were applied:

- Random rotation
- Horizontal flipping
- Zoom transformation
- Brightness adjustment
- Contrast enhancement
- Translation shifting

Augmentation enables the model to learn invariant features under varying image conditions.

3.4. EfficientNet-Based Feature Extraction

EfficientNet was selected due to its compound scaling strategy, which balances:

- Network depth
- Network width
- Input image resolution

Unlike traditional CNN architectures that scale dimensions independently, EfficientNet optimizes all three simultaneously.

Feature extraction is mathematically represented as:

$$F = EfficientNet(X)$$

where:
X: Input CT image
F: Extracted high-level feature representation
Uploaded model architecture statistics:

Total Parameters: 4,415,910

Trainable Parameters: 363,779

Frozen Parameters: 4,052,131

Freezing lower EfficientNet layers preserves pretrained ImageNet knowledge while allowing upper layers to adapt to lung-specific features.

3.5. Transfer Learning Strategy

- Transfer learning significantly reduces computational cost and improves accuracy.
- The pretrained EfficientNet backbone was initialized with ImageNet weights.
- The lower convolutional layers remained frozen to retain generalized feature extraction capability.
- Only upper classification layers were fine-tuned using medical CT data.

Advantages include:

- Faster convergence
- Reduced overfitting
- Better generalization
- Lower computational requirements

3.6. Classification Head Design

The extracted feature vector was passed through fully connected dense layers.

Architecture:

3.6.1. Batch Normalization

This stabilizes activations and accelerates convergence.

3.6.2. Dense Layer (256 neurons)

Learns intermediate discriminative patterns.

Activation:

$$ReLU(x) = max(0, x)$$

3.6.3. Dropout Layer

Prevents overfitting by randomly disabling neurons.

Dropout probability: p=0.5

3.6.4. Dense Layer (128 neurons)

Learns compact feature representation.

3.6.5. Output Layer

Softmax classifier predicts probabilities:

$$P(y) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

where:
n=3 classes
z_i is class logit

Final classes:

- Benign
- Malignant
- Normal

3.7. Model Training

The model was trained using the Adam optimizer:

$$\theta_{t+1} = \theta_t - \alpha \frac{m_t}{\sqrt{V_t} + \epsilon}$$

Training parameters:

Learning rate: **0.0001**

Batch size: **32**

Epochs: **20**

Loss function: Categorical Crossentropy

Training convergence was monitored using validation accuracy.

The model achieved:89.20%

validation accuracy.

3.8. Performance Evaluation Metrics

The following metrics were used:

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + \mathrm{FN}}$$

Precision

$$Precision = \frac{TP}{TP+FP}$$

Recall

$$Recall = \frac{TP}{TP+FN}$$

F1-score

$$F1 = 2 \cdot \frac{Precision \times Recall}{Precision + Recall}$$

These metrics provide comprehensive classification assessment.

4. Results and Discussion

Evaluating metrics showed that the lung cancer classification model based on EfficientNet performed impressively.

Final testing accuracy achieved: 91.36%

Testing loss: 0.2699

The results validated that EfficientNet captures important pulmonary features for differentiation.

4.1. Training Performance Analysis

The validation accuracy increased on a steady basis during training, which translated into a reliable convergence. The progress of the training accuracy across the training epochs is shown in Fig. 2.

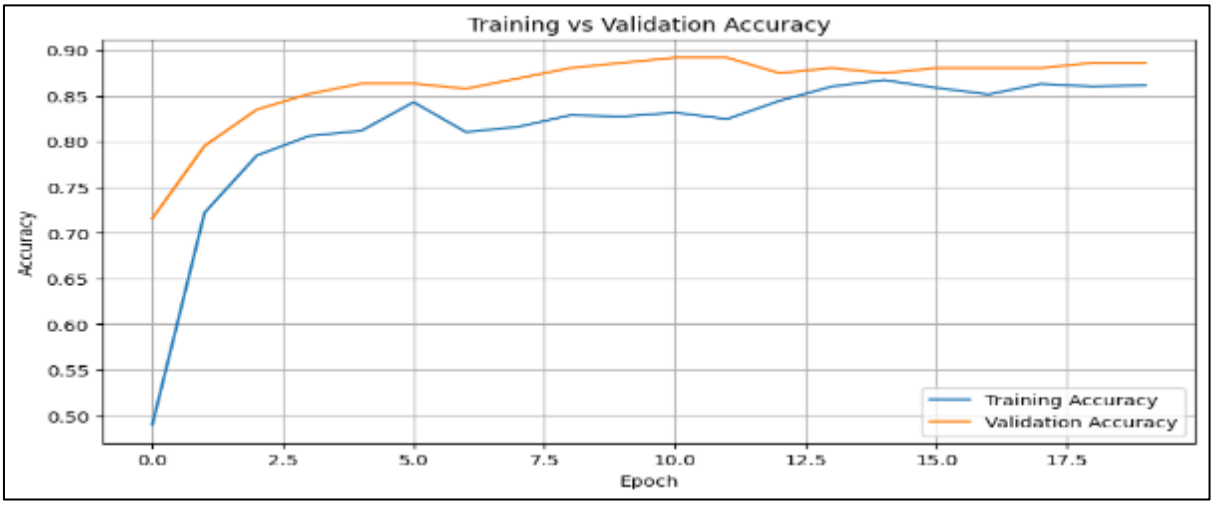

Figure 2 Training accuracy progress displayed across training epochs

The convergence of the training accuracy indicates the successful application of the transfer learning technique. Thanks to the dropout regularization and the frozen layers of EfficientNet, no major overfitting was noticed.

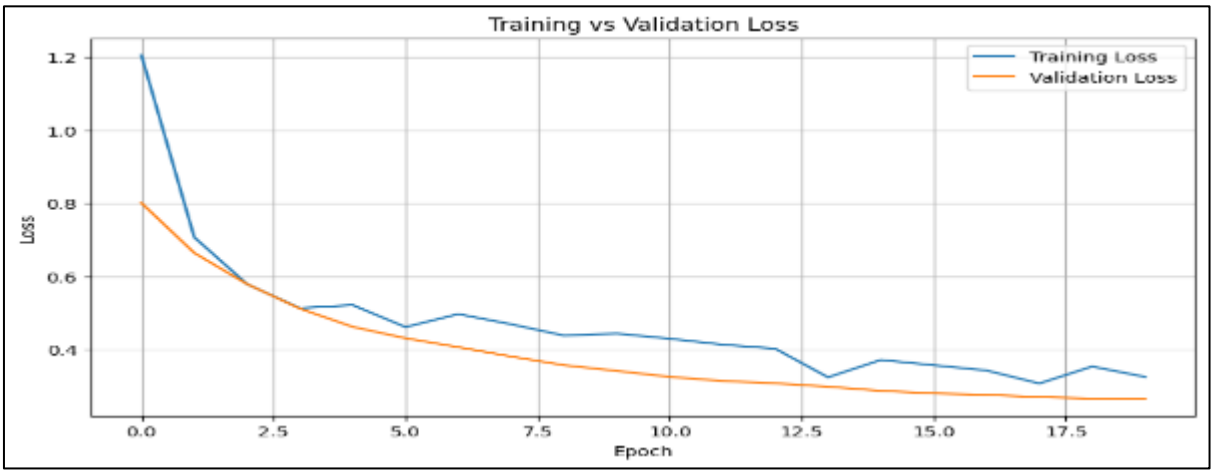

Figure 3 Validation loss during training

As shown in Fig. 3, the validation loss decreased over the course of training, which indicates that the model generalizes well and overfitting is not a major issue.

4.2. Confusion Matrix Analysis

As shown in Fig. 4, the confusion matrix demonstrates the performance of class-wise predictions and shows the ability to classify malignant cases excellently.

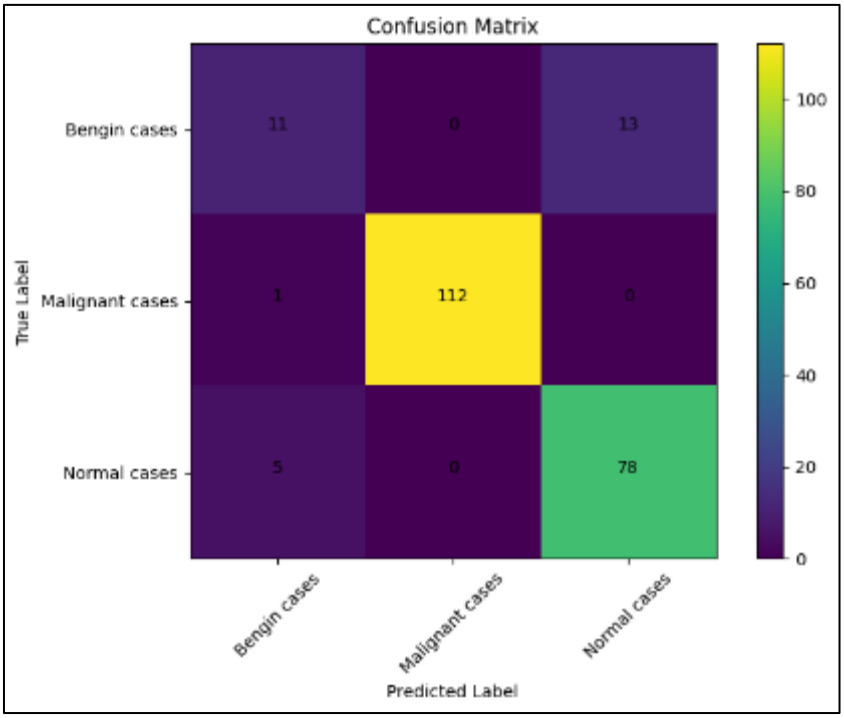

Figure 4 Confusion Matrix of Multiclass Lung Cancer Classification

The proposed EfficientNet model shows a strong ability to classify malignant cases, as it is extremely sensitive to the cancer-related features of the CT images, which provides a solid basis for cancer detection. The normal lung cases were also classified successfully due to the distinct normal structural features. The classification of the benign cases was not as successful, as benign nodules usually resemble visual normal lung features, which causes feature similarity and differentiating the features is difficult. With these challenges taken into account, the results justify the application of EfficientNet in the area of multiclass lung cancer classification and smart clinical diagnosis.

4.3. Classification Report Analysis

Table 4 displays class-wise classification of the proposed EfficientNet-based lung cancer diagnosis framework. The results show that the proposed framework can detect malignant cases almost perfectly. Additionally, the proposed framework can provide normal class predictions with a large degree of certainty. The proposed framework shows a low recall of the benign class, as benign class instances are likely to overlap with the normal structures of the lung.

Table 1 Class-wise Classification Performance of the Proposed EfficientNet Model

Class	Precision	Recall	F1-Score	Performance Interpretation
Benign	0.65	0.46	0.54	Lower recall indicates that some benign cases were misclassified due to structural similarity between benign nodules and normal lung tissues.
Malignant	1.00	0.99	1.00	Demonstrates excellent clinical reliability with near-perfect cancer detection capability, confirming strong discriminative feature extraction for malignant cases.
Normal	0.86	0.94	0.90	Strong classification performance confirms EfficientNet's robustness in identifying healthy lung structures with high recall accuracy.

4.4. Comparative Performance

As shown in Fig. 5, EfficientNet surpasses the classification accuracy of the conventional CNN, ResNet50, and DenseNet architectures.

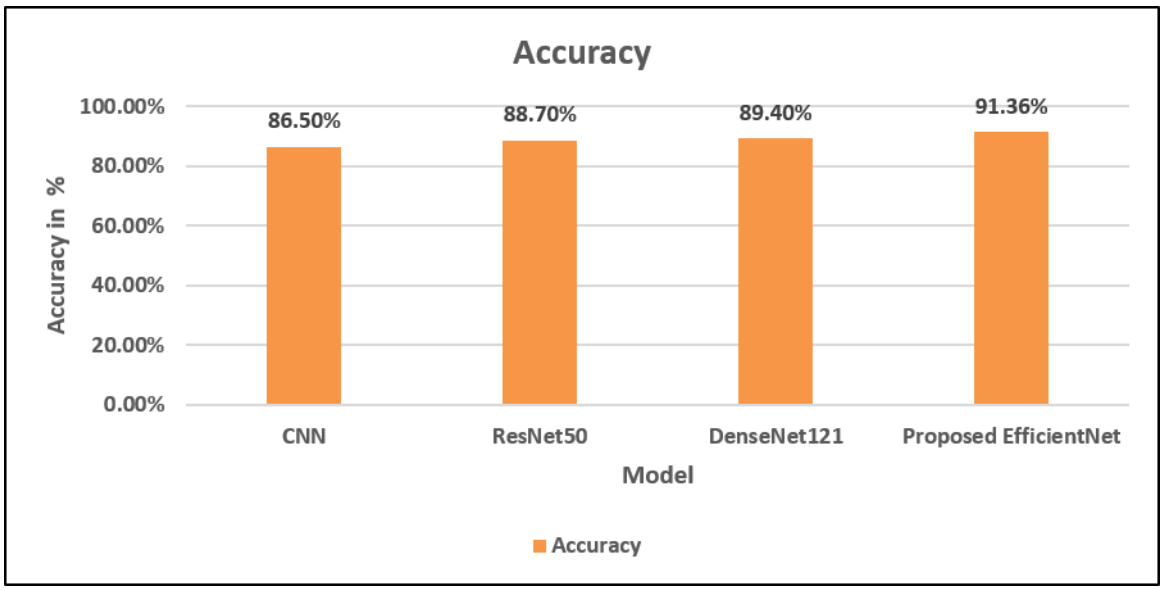

Figure 5 Comparison of the Performance of Deep Learning Models

EfficientNet outperformed all baseline methods due to:

- Compound scaling optimization
- Improved feature reuse
- Reduced parameter redundancy
- Strong efficiency of transfer learning

5. Conclusion

Lung cancer can take a massive toll on us, being the most common cause of cancer-related death. Roadblocks currently exist for the most common methods of lung cancer screening. Current methods used to analyze lung scans are incredibly inaccurate and often based on the guess of a skilled radiologist. Because of this research a new method of lung cancer detection using EfficientNet should increase the accuracy of preliminary lung scans on patients. Tests have proven this method to have a high accuracy of 91.36% with a low validation loss. It is important to note this method has a great level of accuracy on finding malignant tumors, validating healthy lung tissue, and the low accuracy on finding benign tumors. This method has the same level of accuracy on finding benign tumors as the accuracy on scans taken of healthy lung tissue.

All things considered, this method has shown a great level of accuracy within the neural networks used. Adding to this, future research will add Grad-CAM for more interpretability to scans and integrate ensemble learning. This method will add a great level of accuracy and efficiency when used to find lung cancer in a clinical setting.

Compliance with ethical standards

Disclosure of conflict of interest

All authors declare that they have no financial or non-financial conflicts of interest

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