Enhanced Diagnosis of Lung Cancer through an Ensemble Learning Model leveraging an Adaptive Optimization Algorithm

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ABSTRACT

Early and accurate diagnosis of lung cancer is crucial to improving patient outcomes and survival rates. Machine and deep learning models have emerged as promising tools to improve the accuracy and efficiency of disease diagnosis. However, achieving optimal diagnostic performance remains a challenging task in medical research. This study integrates ensemble learning techniques with an adaptive optimization algorithm to enhance the accuracy of lung cancer diagnosis. By combining the predictive potential of multiple base classifiers, the ensemble-learning model improves overall performance and mitigates the weaknesses of individual classifiers. Additionally, the adaptive optimization algorithm dynamically adjusts the model parameters to optimize the classification performance. The effectiveness of the approach was evaluated using a comprehensive dataset that includes lung cancer images. Rigorous evaluation and comparison with state-of-the-art models showed that the proposed method achieved superior diagnostic performance, reaching an overall accuracy of 99%.

Keywords-lung cancer diagnosis; ensemble learning; classification; adaptive optimization algorithm

I. INTRODUCTION

Lung cancer was the most diagnosed cancer in 2022 with an estimated 2.5 million new cases (12.4%) [1]. It remained the leading cause of cancer-related death, with an estimated 1.8 million deaths (18.7%). One of the main reasons for this high mortality rate is that lung cancer is often not diagnosed until it is in an advanced stage, losing the best chance for surgical intervention [2]. Traditional diagnostic methods rely on the review of CT images by physicians, which often have many limitations in sensitivity and specificity [3], underscoring the critical need for innovative computational techniques to improve clinical decision-making in this domain. In recent years, Deep Learning (DL) techniques, such as Convolutional Neural Networks (CNNs), have emerged as promising tools to improve the accuracy and efficiency of disease diagnosis, including lung cancer. These techniques leverage the analysis of complex datasets to extract meaningful patterns and facilitate informed decision-making [4]. More recently, transformers have been introduced as an alternative to CNNs [5, 6]. Transformers apply an attention mechanism to understand the global relationships among features and have shown great potential in medical imaging applications, as they have flourished in natural language processing and computer vision [7, 8].

Recent advances in medical imaging have demonstrated the potential of CNN and ViT architectures to achieve superior performance in lung cancer diagnosis compared to interpretations by trained radiologists. However, despite notable strides in this direction, achieving optimal diagnostic performance remains a challenging frontier in medical research. To overcome these challenges, ensemble learning has garnered considerable attention for its ability to integrate diverse base classifiers to create a stronger and more accurate predictive model, thus enhancing predictive performance and robustness for tasks such as lung cancer detection. However, the efficacy of this technique depends critically on the model parameters. Setting up these parameters manually would be a tedious task and could result in suboptimal performance and limited generalizability. To address these challenges, this study used adaptive algorithms, which are largely considered in similar situations due to their ability to dynamically adjust model parameters based on real-time feedback, optimizing performance across diverse patient populations and data distributions.

This study introduces a novel framework to enhance lung cancer diagnosis through the integration of ensemble learning techniques with an adaptive optimization algorithm. The main contributions of our work are summarized as follows: (i) improve the predictive performance and robustness of individual DL models using an ensemble learning technique, and (ii) optimize the model parameters using adaptive algorithms. By leveraging the complementary strengths of ensemble learning and adaptive optimization, this approach aims to mitigate the limitations of conventional diagnostic methods and improve the accuracy, sensitivity, and specificity of lung cancer detection. The efficacy of the proposed approach was evaluated through a comprehensive evaluation using a real-world clinical dataset and comparing its performance with previous state-of-the-art methods.

II. BACKGROUND

A. Lung Cancer

Lung cancer is one of the most common cancers worldwide and is a leading cause of cancer-related deaths. The two main types of lung cancer are Non-Small Cell Lung Cancer (NSCLC) and Small Cell Lung Cancer (SCLC).

1) Non-Small Cell Lung Cancer (NSCLC)

NSCLC is the most common type of lung cancer, accounting for approximately 85% of all cases. Common types of NSCLC include:

- Adenocarcinoma: it is the most common type of lung cancer. It is usually found in the outer or peripheral areas of the lung and is more likely to be found before it has spread. Even if adenocarcinoma occurs mainly in people who smoke or used to smoke, it is also the most common type of lung cancer diagnosed in people who do not smoke.
- Squamous cell carcinoma: this type of lung cancer manifests most frequently in the central part of the lungs, near the bronchial tube.
- Large cell carcinoma: large cell carcinoma is a less common subtype and can occur in any part of the lung. It tends to grow and spread more rapidly than adenocarcinoma or squamous.

Figure 1 presents samples of images illustrating the three types of NSCLC.

2) Small Cell Lung Cancer (SCLC)

SCLC accounts for about 15% of lung cancers. This type of lung cancer is highly aggressive and tends to spread quickly to other parts of the body.

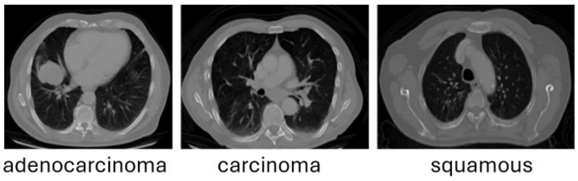

Fig. 1. Lung cancer types.

Lung cancer typically does not cause signs or symptoms in its earliest stages. Signs and symptoms (e.g. coughing, chest pain, shortness of breath, and unexplained weight loss) typically occur when the disease is advanced. Several risk factors increase the likelihood of developing lung cancer: tobacco smoking, exposure to harmful substances, previous radiation therapy, and having a family history of lung cancer. Some of these risks can be controlled.

B. Related Works

Lung cancer diagnosis has attracted more and more research in the past two decades. These works can be broadly classified according to their objectives into three main categories: lung nodule segmentation, lung nodule detection, and lung nodule classification. For lung nodule segmentation, it is largely considered a prerequisite to provide accurate lung CT image analysis. The aim is to recognize the voxel information and the external contour of the region of interest. Various deep learning-based methods have been proposed for lung nodule segmentation. In [9], a Dual-Branch Residual Network (DB-ResNet) was proposed, which simultaneously captured the multiview and multiscale features of different nodules in CT images. DB-ResNet was evaluated on the LIDC-IDRI dataset and achieved an 82.74% Dice Similarity Coefficient (DSC). In [10], Dense R2Unet (dense recurrent residual CNN) was introduced, built on the U-Net and dense interconnections. The findings showed better segmentation performance compared to traditional UNet and Residual UNet. ResNet-34 was used in [11] to extract the lung region and surroundings from a chest X-ray image. Then, the YOLO object detection model was used to detect common lung abnormalities, such as aortic enlargement, calcification, and others.

Lung nodule detection consists of two main stages: (i) nodule candidate generation, and (ii) False Positive Reduction (FPR). The first stage aims to find lung nodule candidates and regions of interest that may help to improve the classification of CT scans. The second stage (FPR) aims to make the detection more precise. In [12], a Two-Stage CNN (TSCNN) was proposed for lung nodule detection. During the first stage, an improved U-Net segmentation network was established. The second stage was built on a 3DCNN classification network for false positive reduction. Experiments were carried out using the LUNA dataset, showing competitive detection performance.

Regarding the classification of lung nodules, the aim is usually to classify a lung CT scan image as normal or abnormal. In [13], a hybridization approach was proposed, which combined the strengths of the CSABC Optimizer and SVM model to create a powerful lung cancer predictive model. In [14] a saliency-based capsule network was proposed to detect lung cancers using CT scan images as input. This approach tuned a pre-trained model and optimized its accuracy using the whale algorithm. The LUNA-16 and LIDC datasets were used to evaluate its accuracy. The experimental results showed high performance, outperforming the most common CNN models such as Inception, Resnets-50, VGG-16, and others. In [15], an ensemble method was proposed, which utilized three distinct models, namely Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR). The predictions from each classifier were combined using majority voting to produce the ensemble classifier. Based on the aforementioned proposals, it is clear that although there were multiple attempts at lung cancer diagnosis, several shortcomings persist, such as:

- There is duplication (reproduction) of research and development efforts instead of benefiting from existing approaches.

- Despite the success of CNNs, challenges persist in achieving optimal diagnostic performance.
- There is a lack of a single conceptual framework to help developers who are not trained in the field of deep learning.

To address these limitations, this study presents an ensemble-learning model leveraging an adaptive optimization algorithm to dynamically adjust model parameters and enhance performance across diverse datasets and clinical settings.

C. *Deep Learning Models*

This study considered three deep learning models for the ensemble learning framework:

- EfficientNet [16] is a family of CNN architectures that were developed by Google AI researchers for efficient model scaling. It achieves state-of-the-art accuracy on various image classification tasks while simultaneously reducing the number of parameters and computational resources required compared to traditional CNNs. Compound scaling is the key idea behind EfficientNet architecture, which aims to increase training speed and parameter efficiency by scaling the model dimensions (depth, width, and resolution) using a small grid search.
- The Swin Transformer [17] is a transformer-based deep learning model that improves the original ViT by introducing two key concepts: hierarchical feature maps and shifted window attention. In the first concept, the input image is partitioned into non-overlapping patches treated as tokens. The features of each token are then set as a concatenation of the raw pixel RGB values. These patches are converted linearly into C-dimensional vectors and then merged into bigger ones as the network gets deeper. The patch merging layer combines the features of each group of 2×2 neighboring patches and merges them into one new window, down-sampling feature map size by 2× and increasing the depth of each patch by 2. This helps to capture both local and global features effectively. Regarding the shifted window attention mechanism, the self-attention is calculated only within non-overlapping windows and not globally as in the ViT model. To capture attention across windows, all windows are shifted by half their height and width, and self-attention is recomputed for the shifted window.
- InceptionV3 [18] is a 48-layer deep pre-trained convolutional neural network model that makes several improvements, including the use of label smoothing, factorized 7×7 convolutions, and an auxiliary classifier to propagate label information lower down the network. The key building block is an Inception module that facilitates the parallel processing of feature maps at different spatial scales. These models are composed of multiple parallel convolutional pathways of varying kernel sizes. This design allows the network to capture spatial hierarchies at different scales, facilitating robust feature extraction. Using factorized convolutions, Inception V3 decomposes standard convolutions into smaller operations, reducing the number of parameters and computational burden and enabling efficient training and inference.

D. *Ensemble Learning*

Ensemble learning is a powerful technique used to improve the performance of a classifier by combining the contribution of multiple trained models to solve the same problem. Several ensemble methods have been proposed. The most common types are:

- Bagging involves training different models and the final prediction is made by averaging or voting.
- Boosting involves sequentially training different learning models on the same data. Each subsequent model corrects the errors made by the previous ones.
- Stacking involves training different learning models and then using a meta-model to learn how to best combine their predictions.

This study opted for the stacking approach due to its efficiency while using strong, diverse base models. In addition, the use of the second meta-learner is likely to discover the best combination of base learners than the voting or average technique used in bagging or boosting.

III. PROPOSED METHODOLOGY

A. *Overall Architecture*

Figure 2 presents the overall architecture of the proposed approach for early diagnosis of lung cancer. The approach goes through mainly three stages. In the first, a set of preprocessing techniques is applied to the original image to enhance its quality. Then, the learning transfer mechanism is used to extract the features of the processed image. In the last stage, an ensemble learning model was trained on the dataset to build the classification model.

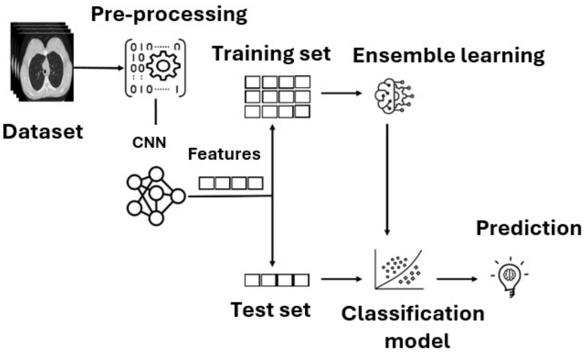

Fig. 2. Overall workflow diagram of the proposed architecture.

B. *Data Preprocessing*

The preprocessing of the dataset aims to clean up the images and transform them into the most suitable format for manipulating data and building classification models. This study used contrast adjusting and denoising.

Contrast adjustment aims to remap the original image intensities to produce higher contrast and consequently enhance image quality. Histogram equalization was employed to adjust image intensities and contrast using the Contrast Limited Adaptive Histogram Equalization (CLAHE) [19] method. This choice can be justified by the fact that CLAHE is largely considered an effective technique for improving image contrast while avoiding over-amplification of noise and preserving image details. The main idea behind CLAHE is that histogram equalization must be performed locally, in smaller regions of the image, rather than globally. The original image is divided into small blocks called tiles. These tiles are then used to perform a histogram equalization with a predefined clip limit. Should any histogram bin values be higher than the clip limit, it will be cut (clipped) and distributed uniformly to other bins.

Denoising aims to recover a noise-free image from its noisy counterpart. In this context, filtering is extensively considered to remove the unwanted signal from an image, called noise, and enhance its quality. Several studies have been proposed to examine the effectiveness of various types of filters applied to different types of medical images (MR, CT, mammography, etc.). In [20], the Adaptive Median Filter (AMF) was effective in removing noise from CT scan images while maintaining the edges and details of the objects. This study used this type of filter for the denoising step.

C. Feature Extraction and Selection

The data features used to train a deep learning model have a huge influence on its performance. Removing irrelevant or partially relevant features and focusing only on the most important ones is likely to improve model performance while accelerating its training time. A variety of techniques can be found for feature extraction and selection. In the context of image processing, CNNs are commonly used to extract relevant features from an image. CNNs that are trained and evaluated on large datasets (e.g. ImageNet) can be reused partly or wholly on different but somehow similar problems. Such a mechanism, so-called Transfer Learning, aims to acquire the knowledge a pre-trained neural network has gathered training on a specific task to solve a different but related task. The benefits of using transfer learning as a feature extractor are mainly related to decreasing training time and resulting in higher performance. The general process for using transfer learning as a feature extractor involves:

- Select and load a pre-trained model that has been trained on a large dataset (e.g., VGG, ResNet, and Inception).
- Freeze the early layers of the model that capture general features.
- Fine-tune the later layers for the specific task.
- Use the pre-trained model for feature extraction by passing the data through it and extracting the output from one or more layers before the removed classification layer.

This study used the Inception V3 module to extract features from the images. This choice can be justified by the flexibility and accuracy of this model.

D. Ensemble Learning

The stacking approach was used to implement ensemble learning. This choice can be justified by the efficiency that this approach provides while using strong, diverse base models. Figure 3 shows the structure of the stacking ensemble learning module.

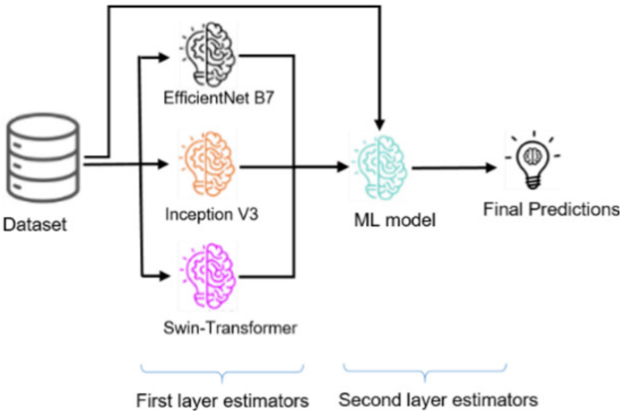

Fig. 3. Stacking architecture.

Regarding the models selected as base learners, three base classifiers were selected due to their efficiency and speed in training. Deep learning models are usually time-consuming, and combining more than one model might increase computing complexity. The selection of these three models was based on the results they provided according to Table I. The selected models were Swin-Transformer, EfficientNetV2, and InceptionV3. The SVM classifier was used as a meta-learner, which is widely used in ensemble learning due to its prediction power. The results presented in Table III show that the SVM classifier outperformed the other machine-learning models. The whole process started by feeding the preprocessed dataset into the three base classifiers in the first-layer estimator. Their results were then forwarded to the meta-classifier used in the second-layer estimator to get the result of the prediction. The findings were then compared to those of the baseline learners and other current approaches to lung cancer detection.

E. Parameter Selection Based on Genetic Algorithm (GA)

Achieving the best performance and generalization in a machine learning model typically requires choosing the optimal hyperparameter values. Manually performing such a task is usually time-consuming. A well-known technique to perform such a task is to leverage appropriate optimization algorithms. This study used a Genetic Algorithm (GA), which is commonly used to solve similar problems. Inspired by the process of natural selection and genetics, a GA is an iterative process that addresses optimization and search problems. The process starts by generating an initial population solution to the optimization problem. Each solution is represented as a chromosome or genotype, which is typically expressed as a series of binary digits. Then, a fitness function is evaluated for each solution to rate its effectiveness with regard to the problem's objective. Individuals with higher fitness values are more likely to be selected for further processing. Next, a genetic operator known as crossover is applied. In this step, genetic information is exchanged between pairs of selected individuals to create new solutions. After that, a small random change in genetic information is introduced to help maintain genetic diversity within the population, preventing premature convergence to suboptimal solutions. Individuals in the current population will be replaced by newly generated ones, and the process reiterates until a termination condition is met, such as reaching a desired fitness level or exceeding a specified number of iterations. As mentioned above, this paper uses SVM as a meta-classifier for the ensemble learning framework. In this classifier, the Radial Basis Function (RBF) kernel is the most popular and widely used because of its versatility. In such a classifier, the regularization parameters C and γ play crucial roles in determining the model's performance and behavior. A GA-based approach was used for this task. The adopted fitness function is described in (1).

$$Fitness = Accuracy\,(params, X, y) \qquad (1)$$

This fitness function uses 5-fold cross-validation to evaluate the classification accuracy of an SVM classifier with the specified hyperparameters C and γ. The mean accuracy across all folds is returned as the fitness value.

IV. EXPERIMENTS

Extensive experiments were carried out on a benchmark dataset to demonstrate the effectiveness of the proposed approach. The experimental procedure started by collecting a publicly available lung cancer dataset [21]. Then, the five deep learning models were trained, collecting their performance metrics. This step aimed to identify the best three models to be used as base learners. In the next step, four machine learning models were trained to identify the best one to be used as a meta-learner. The SVM model was selected. To efficiently select the SVM hyperparameters, the GA algorithm was applied to select the best C and γ values. Finally, the results were compared with some well-referenced related works.

A. Data Description

The IQ-OTH dataset [21] was collected at the Iraq-Oncology Teaching Hospital (IQ-OTH) and the National Center for Cancer Diseases (NCCD). It includes CT scans of patients diagnosed with lung cancer at different stages, as well as healthy subjects. The dataset contains a total of 1190 images representing CT scan slices grouped into three classes: normal, benign, and malignant. The CT scan distribution is 416 images for the normal class, 120 images for the benign class, and the rest for the malignant class. The imbalanced distribution of the images may lead to misleading accuracy. To overcome such a problem, data augmentation was performed using the resampling technique. The minority class was oversampled to obtain a balanced distribution of all target classes. Figure 4 shows example data from the dataset.

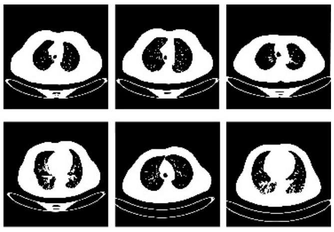

Fig. 4. Example of CT scan images.

B. Experimental Setting

- Configuration: Google Colab, Python version 3.10.12, and Tensorflow 2.13 with Keras API were used. For the implementation of deep learning models, their built-in version in the keras.applications package was used. The learning rate was initially set at 0.001 and the Adam optimizer was selected as the initial optimizer. The size of each training batch and the number of epochs were selected using GA.
- Performance Metrics and Evaluation: Accuracy, precision, recall, and F1 score were calculated to evaluate the performance of the proposed model. Their mathematical expressions are as follows:

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

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

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

$$F1 - score = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

where TP refers to True Positives, FP refers to False Positives, TN refers to True Negatives and FN refers to False Negatives.

C. Comparison between Deep Learning Models

This section highlights the results obtained through a set of the most common deep learning models. The aim was to select the best three models to be used in the ensemble learning framework. Table I shows the accuracy, precision, recall, and F1 score results of all models for the IQ-OTH dataset.

TABLE I. DIFFERENT DEEP LEARNING ARCHITECTURES' PERFORMANCE IN PREDICTING LUNG CANCER

ML model	**Performance metrics**			
	Accuracy	**Precision**	**Recall**	**F1 score**
Resnet50	91	89	90	90
VGG16	90	88	89	89
InceptionV3	95	95	95	95
EfficientNetV2S	92	88	89	88
Swin-Transformer	96	95	95	95

EfficientNetV2, Inception, and Swin-Transformer were more accurate than the other models. Hence, these three models were selected to be the base learners in the ensemble learning framework.

D. Evaluation of Machine Learning Models for Classification

The performance of the SVM classifier for the lung cancer classification task was compared with several other popular machine learning algorithms, including K-Nearest Neighbors (KNN), Decision Tree (DT), and Naive Bayes (NB).

TABLE II. PERFORMANCE COMPARISON OF VARIOUS MACHINE LEARNING ARCHITECTURES IN PREDICTING LUNG CANCER.

ML model	**Performance metrics**			
	Accuracy	**Precision**	**Recall**	**F1 score**
DT	85	90	89	89
NB	81	95	75	78
KNN	89	91	93	92
SVM	89	89	94	93

The SVM demonstrated better performance than the other models. Although models such as KNN also performed well, they might suffer from overfitting when dealing with high-dimensional data or when the dataset is imbalanced. It is worth mentioning that the performance of SVM strongly depends on the selection of appropriate hyperparameters, such as the choice of kernel function and regularization parameters. Improper selection of these parameters can lead to suboptimal results or even poor generalization.

E. Assessment of Genetic Algorithm (GA)-based Optimization

Table III presents the GA parameters that were used during the implementation of the genetic operations.

TABLE III. GENETIC ALGORITHM PARAMETERS.

Property	Value/Method
Size of generation	100
Initial population size	30
Selection method	Tournament
Number of crossover point	1
Mutation method	Uniform mutation
Mutation probability	0.05

Table IV shows that the SVM classifier's performance improved significantly when its hyperparameters were optimized using GA. GA efficiently explored the hyperparameter space, often converging to optimal or near-optimal solutions in a few evaluations.

TABLE IV. CLASSIFICATION RESULTS BASED ON ADAPTIVE GENETIC ALGORITHM (GA)

C-value	Gamma	Accuracy
1	5	95
20	35	96
360	100	94
19	3	99

F. Comparison with State-of-the-Art Models

Table V presents the accuracy rates of previous state-of-the-art models in the same domain.

TABLE V. COMPARISON WITH STATE-OF-THE-ART MODELS.

Model	Accuracy (%)
Proposed model	99
[22]	93.54
[23]	89.88
[24]	99
[25]	98.74
[26]	95

These results show that the proposed ensemble learning model outperforms most of the state-of-the-art models, except the model in [24] which had almost the same accuracy. These results indicate that the proposed model offers significant improvements in diagnostic accuracy and early detection compared to conventional models and state-of-the-art proposals. The use of ensemble learning empowered by the adaptive algorithm demonstrated a marked increase in the early detection of lung cancer. However, it should be noted that this is a preliminary study, and many more experiments with larger datasets are required for generalization. Future studies should investigate developing a fully automated framework that can automatically classify CT scans as normal, benign, or malignant. This is a common limitation in other studies for lung cancer diagnosis.

V. CONCLUSIONS

This study highlighted the importance of utilizing an ensemble learning framework, augmented by an adaptive optimization algorithm, to enhance lung cancer diagnosis. The findings indicate that this innovative approach outperformed conventional diagnostic techniques, offering substantial potential to increase early detection rates and ultimately improve survival rates for patients facing this deadly disease. The ability of ensemble models to combine multiple algorithms enables a more robust analysis of complex medical imaging data, while adaptive optimization ensures that model parameters are fine-tuned for optimal performance. Although this study made significant strides in advancing the diagnosis of lung cancer, there are several avenues for future exploration and refinement. An important direction for future research includes the investigation of integrating multimodal data sources, such as radiological images, genomic data, and clinical metadata, into such models.

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REFERENCES

[1] H. Sung *et al.*, "Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries," *CA: A Cancer Journal for Clinicians*, vol. 71, no. 3, pp. 209–249, 2021, https://doi.org/10.3322/caac.21660.

[2] N. Horeweg *et al.*, "Detection of lung cancer through low-dose CT screening (NELSON): a prespecified analysis of screening test performance and interval cancers," *The Lancet Oncology*, vol. 15, no. 12, pp. 1342–1350, Nov. 2014, https://doi.org/10.1016/S1470-2045(14)70387-0.

[3] B. Prabhakar, P. Shende, and S. Augustine, "Current trends and emerging diagnostic techniques for lung cancer," *Biomedicine & Pharmacotherapy*, vol. 106, pp. 1586–1599, Oct. 2018, https://doi.org/10.1016/j.biopha.2018.07.145.

[4] L. Wang, "Deep Learning Techniques to Diagnose Lung Cancer," *Cancers*, vol. 14, no. 22, Jan. 2022, Art. no. 5569, https://doi.org/10.3390/cancers14225569.

[5] A. Vaswani, "Attention is all you need," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[6] C. Matsoukas, J. F. Haslum, M. Söderberg, and K. Smith, "Is it Time to Replace CNNs with Transformers for Medical Images?" arXiv, Aug. 20, 2021, https://doi.org/10.48550/arXiv.2108.09038.

[7] L. B. Ammar, K. Gasmi, and I. B. Ltaifa, "ViT-TB: Ensemble Learning Based ViT Model for Tuberculosis Recognition," *Cybernetics and Systems*, vol. 55, no. 3, pp. 634–653, Apr. 2024, https://doi.org/10.1080/01969722.2022.2162736.

[8] W. Wenxuan, C. Chen, D. Meng, Y. Hong, Z. Sen, and L. Jiangyun, "Transbts: Multimodal brain tumor segmentation using transformer," in *International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer*, 2021, pp. 109–119.

[9] H. Cao *et al.*, "Dual-branch residual network for lung nodule segmentation," *Applied Soft Computing*, vol. 86, Jan. 2020, Art. no. 105934, https://doi.org/10.1016/j.asoc.2019.105934.

[10] K. Dutta, "Densely Connected Recurrent Residual (Dense R2UNet) Convolutional Neural Network for Segmentation of Lung CT Images." arXiv, Feb. 01, 2021, https://doi.org/10.48550/arXiv.2102.00663.

[11] H. T. Nguyen, M. N. Nguyen, S. C. Pham, and P. H. D. Bui, "Abnormalities detection on chest radiograph with bounding box-based lungs extraction and object detection algorithm," *International Journal of Information Technology*, vol. 16, no. 4, pp. 2241–2251, Apr. 2024, https://doi.org/10.1007/s41870-023-01687-9.

[12] H. Cao *et al.*, "A Two-Stage Convolutional Neural Networks for Lung Nodule Detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 7, pp. 2006–2015, Jul. 2020, https://doi.org/10.1109/JBHI.2019.2963720.

[13] S. Tared, L. Khaouane, S. Hanini, A. Khaouane, and M. Roubehie Fissa, "Enhancing lung cancer prediction through crow search, artificial bee colony algorithms, and support vector machine," *International Journal of Information Technology*, vol. 16, no. 5, pp. 2863–2873, Jun. 2024, https://doi.org/10.1007/s41870-024-01770-9.

[14] K. Ramana *et al.*, "Early Prediction of Lung Cancers Using Deep Saliency Capsule and Pre-Trained Deep Learning Frameworks," *Frontiers in Oncology*, vol. 12, Jun. 2022, https://doi.org/10.3389/fonc.2022.886739.

[15] O. Singh and K. K. Singh, "An approach to classify lung and colon cancer of histopathology images using deep feature extraction and an ensemble method," *International Journal of Information Technology*, vol. 15, no. 8, pp. 4149–4160, Dec. 2023, https://doi.org/10.1007/s41870-023-01487-1.

[16] M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," in *Proceedings of the 36th International Conference on Machine Learning*, May 2019, pp. 6105–6114.

[17] Z. Liu *et al.*, "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows," in *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, Montreal, QC, Canada, Oct. 2021, pp. 9992–10002, https://doi.org/10.1109/ICCV48922.2021.00986.

[18] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, Jun. 2016, pp. 2818–2826, https://doi.org/10.1109/CVPR.2016.308.

[19] K. Zuiderveld, "Contrast limited adaptive histogram equalization," in *Graphics gems IV*, USA: Academic Press Professional, Inc., 1994, pp. 474–485.

[20] A. A. Omer, O. I. Hassan, A. I. Ahmed, and A. Abdelrahman, "Denoising CT Images using Median based Filters: a Review," in *2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE)*, Khartoum, Aug. 2018, pp. 1–6, https://doi.org/10.1109/ICCCEEE.2018.8515829.

[21] Hamdalla F. Al-Yasriy, "The IQ-OTH/NCCD lung cancer dataset." Kaggle, https://doi.org/10.34740/kaggle/ds/672399.

[22] H. F. Al-Yasriy, M. S. Al-Husieny, F. Y. Mohsen, E. A. Khalil, and Z. S. Hassan, "Diagnosis of Lung Cancer Based on CT Scans Using CNN," *IOP Conference Series: Materials Science and Engineering*, vol. 928, no. 2, Aug. 2020, Art. no. 022035, https://doi.org/10.1088/1757-899X/928/2/022035.

[23] H. F. Kareem, M. S. Al-Huseiny, F. Y. Mohsen, E. A. Khalil, and Z. S. Hassan, "Evaluation of SVM performance in the detection of lung cancer in marked CT scan dataset," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 3, Mar. 2021, Art. no. 1731, https://doi.org/10.11591/ijeecs.v21.i3.pp1731-1738.

[24] V. R. Nitha and V. S. S. Chandra, "ExtRanFS: An Automated Lung Cancer Malignancy Detection System Using Extremely Randomized Feature Selector," *Diagnostics*, vol. 13, no. 13, Jan. 2023, Art. no. 2206, https://doi.org/10.3390/diagnostics13132206.

[25] C. Yan and N. Razmjooy, "Optimal lung cancer detection based on CNN optimized and improved Snake optimization algorithm," *Biomedical Signal Processing and Control*, vol. 86, Sep. 2023, Art. no. 105319, https://doi.org/10.1016/j.bspc.2023.105319.

[26] S. T. Vemula, M. Sreevani, P. Rajarajeswari, K. Bhargavi, J. M. R. S. Tavares, and S. Alankritha, "Deep Learning Techniques for Lung Cancer Recognition," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 14916–14922, Aug. 2024, https://doi.org/10.48084/etasr.7510.