https://doi.org/10.48047/AFJBS.6.12.2024.1140-1149

African Journal of Biological Sciences
Journal homepage: http://www.afjbs.com
Research Paper Open Access

A critique of CNN Models for the Detection of Early-Stage Lung Cancer

Vinayak
Research Scholor,
Integral University
Lucknow, Uttar Pradesh, India
srmvinayak@gmail.com
Dr. Manish Madhava Tripathi
Integral University
Lucknow, Uttar Pradesh, India
mmt@iul.ac.in
MCN-IU/R&D/2024-MCN0002807

Article History
Volume 6 Issue 12, 2024
Received: 25 May 2024
Accepted : 25 June 2024
doi:
10.48047/AFJBS.6.12.2024.1140-1149

***Abstract*—**Lung cancer continues to be a leading cause of global mortality, with escalating death rates since 1985. Early and precise detection is imperative for enhancing patient survival prospects. This study undertakes a comprehensive examination of automated algorithms for identifying respiratory tumors in their initial stages using CT imagery. CT scans are favored for their efficacy in detecting lung cancer nodules. The investigation assesses diverse methodologies, leveraging datasets such as LIDC, ELCAP, LUNA-16, and AAPM. Segmentation, Feature Extraction, Neural Network Identification, and Image Pre-Processing constitute integral stages in the detection process. By prioritizing ResNet-50 transfer learning models, which have exhibited notable accuracy in detecting COVID-19 and breast cancer, there exists potential to enhance precision and facilitate early-stage cancer prognosis. This review article has the potential to transform lung cancer diagnosis and treatment, potentially providing patients with an easier and more effective path to recovery.

Keywords—Lung Cancer, LUNA 16, Machine Learning, CNN, RESNET 50, Computer Tomography (CT).

I. INTRODUCTION

Lung cancer, significantly influenced by smoking and air pollution, represents a severe global health issue, expected to cause 17 million deaths by 2030. It ranks as the second most prevalent cancer globally, mainly impacting men, with more than 2.5 million new cases in 2023 alone. Considerable research efforts are focused on its early detection [1].

Extensive research has focused on utilizing Machine Learning (ML) and Deep Learning (DL) for the early detection of lung cancer.Classification tasks often employ ML techniques like SVM and K-Nearest Neighbor, while DL thrives in areas like computer vision and speech processing thanks to intricate neural networks, achieving higher accuracy [2].

Recently, Deep Learning techniques, particularly Convolutional Neural Networks (CNNs), have been utilized for early lung cancer detection. The main datasets employed are sourced from Computed Tomography (CT) scans and X-rays.Due to their higher accuracy, CT scans are the preferred dataset. CNNs, which excel in image classification, are particularly effective at processing CT scan images[3].

In the use of CNNs for medical disease detection, there are two common strategies: building models from scratch, which can require significant data and time. Alternatively, Transfer Learning (TL) employs adjustments to pre-existing models such as Alexnet, VGG, ResNet, Inception, DenseNet, and MobileNet. This approach offers computational efficiency and saves resources.

This research focuses on detecting early lung cancer by utilizing pre-trained models on CT images, evaluating their effectiveness through various metrics and comparative analysis. It emphasizes a comprehensive assessment of the performance of various pre-trained models with unique architectural features[4].

II. METHODOLOGY

A. Dataset

Datasets play a vital role in machine learning, particularly in the field of medical imaging. Expert-validated, labeled data is essential for developing effective algorithms for detecting lung cancer. This section delineates the datasets employed in recent research concerning neural networks for detecting lung cancer.

The Lung Image Database Consortium (LIDC-IDRI)

The LIDC-IDRI dataset is an international compilation that includes 1018 cases from diverse educational centers and radiology companies. Each case comes with CT scan annotations in XML format, independently reviewed by four expert thoracic radiologists. The dataset includes 244,527 images from 1010 patients, allowing for diagnosis at both the patient and nodule levels. Nodules are classified into various categories, and comprehensive diagnostic details, such as methods and nodule types, are included.

LUNA16

The LUNA16 dataset, which is a meticulously selected subset of the LIDC-IDRI, comprises approx. 900 CT scans that were chosen based on particular criteria, excluding scans with a slice thickness exceeding 2.5 mm and any irregularities. It contains approx. 36,500 annotations and specifically targets nodules that are 3 mm or larger for lung cancer screening. Annotations that were close enough to overlap were carefully averaged, resulting in counts of 2290, 1602, 1186, and 777 nodules, each reviewed by 1, 2, 3, or 4 radiologists, respectively.

National Lung Screening Trial (NLST)

The National Lung Screening Trial (NLST) was a research project carried out between 2002 and 2004 involving 54,000 participants. It was designed to compare the effectiveness of low-dose CT scans and chest radiography, conducted at annual intervals, in screening for lung cancer. The main goal was to determine if low-dose CT scans could reduce lung cancer mortality rates among high-risk individuals. Outcomes were determined based on the assessment of indeterminate nodules or abnormalities by radiologists. The NLST was a collaborative effort between the Divisions of Cancer Prevention, Treatment, and Diagnosis at the National Cancer Institute[4].

B. CNN architectures

AlexNet

In 2012, a groundbreaking neural network called AlexNet was introduced by three prominent authors, including Alex Krizhevsky. This innovative network architecture features eight layers, which consist of five convolutional layers and three fully connected (FC) layers. It utilizes advanced techniques such as pooling and ReLU activation functions. AlexNet is designed to process input images of dimensions 227 X 227 X 3. The convolutional layers use 11 X 11 filters, and pooling operations are performed with 3 X 3 filters at different stride values[5].

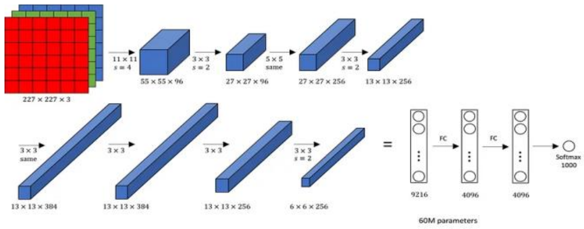

Fig. 1. AlexNet Architecture

The procedure for identifying areas affected by lung cancer using AlexNet includes several crucial steps:

i) Image Loading: Begin by accessing the LIDC IDRI database, which contains 254,727 images from 1080 cases. For training AlexNet, a subset of 2910 images is selected, allocating 70% for training and 30% for validation using the 'split Each Label' function.

ii) Loading AlexNet: Start by initializing the AlexNet architecture and detailing essential aspects of the network. Figure 1 illustrates the development of AlexNet, featuring various parameters such as coefficients, offsets, and padding used in its convolutional, Rectified Linear Unit (ReLU), and pooling layers.

iii) Replacement of the Concluding Layer: Substitute the last convolutional layer with a fully connected (FC) layer to produce classification outputs, and add a softmax layer for further refinement.

iv)Network Training: Use the 'trainNetwork (image datastores, layers, options)' function for image classification. 'Image Datastores' gather the input images, 'layers' define the network structure, and 'options' include settings such as a learning rate of 0.0001, an accuracy goal of 99.91%, a maximum of 6 epochs, and validation frequency every 3 iterations. It also allows for customized plotting and progress monitoring settings specifically designed for lung cancer detection.

v) Image Categorization: The final step involves classifying the output data using validation images, which leads to the determination of accuracy. Figure 2 visually displays these validated images along with their corresponding probability values.

Fig. 2. Problem Identification using AlexNet

Inception V1

The Inception V1 (GoogleNet) architecture employs 1x1, 3x3, and 5x5 filters to process images, reducing the number of parameters from 60 million to 4 million, enhancing its efficiency. Transfer Learning plays a vital role in training image recognition models using GoogleNet, particularly for detecting lung cancer. It effectively classifies images, differentiating between benign and malignant tumors[5].

The procedure includes loading images, reviewing the network architecture, and employing pre-trained models. The base layers are frozen to accelerate training, and the network is trained using various image sizes, achieving an accuracy of 94.10% in 46 hours. Validation is performed to pinpoint cancer-affected areas, with the outcomes offering insights into the accuracy achieved.

VGG 16

Compared to AlexNet, the Oxford Visual Geometry Group (VGG) model is more intricate yet simpler in design. It uses 3x3 filters with a stride of 1, pad, and max pooling across all layers. The layout of the VGG-16 architecture is depicted in Figure 2, featuring three fully-connected layers topped with a SoftMax layer, thirteen convolutional layers, five max-pooling layers, totaling sixteen layers. The final determination of the presence or absence of lung cancer is made by a fully connected layer that includes the SoftMax layer [6].

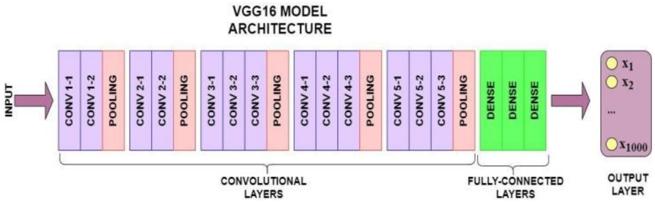

Fig. 3. VGG16 Model Architecture

ResNet50

ResNet-50, short for Residual Network-50, is a groundbreaking convolutional neural network (CNN) that has significantly advanced the field of deep learning. Developed in 2015 by Kaiming He and his team at Microsoft Research Asia, ResNet-50 utilizes deep residual learning to facilitate the training of extremely deep networks with hundreds of layers. The development of ResNet-50 was inspired by a critical insight in deep learning: simply adding more layers to a neural network does not always improve performance, contrary to what was traditionally expected. Although theoretically, more layers should enable the network to incorporate previous layers' knowledge and additional data, this often did not materialize in practice.

In response, the ResNet team introduced a pivotal architectural innovation known as skip connections or residual blocks. These connections allow the network to preserve essential information from earlier layers, enhancing its ability to learn more significant data representations. This design made it possible to effectively train networks with up to 152 layers. Achieving remarkable outcomes, such as a low 3.57% error rate on the ImageNet dataset and victories in prestigious competitions like the COCO and ILSVRC object detection challenges, this architectural innovation has solidified ResNet's prominent role and potential in the deep learning arena. ResNet-50, with its 50 layers organized into five blocks containing residual blocks, excels in training exceedingly deep networks and consistently delivers top-tier results in tasks such as object detection, image classification, and image segmentation. The distinctive skip connections of ResNet-50 are crucial for effective information retention and learning. With these advancements, ResNet-50 marks a significant breakthrough in deep learning, transforming the capabilities of neural networks in computer vision tasks [7].

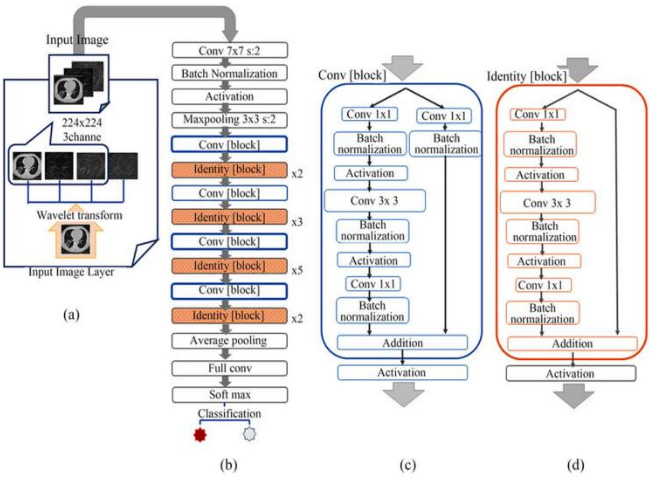

Fig. 4. ResNet50 Model Architecture

III. THEMATIC OVERVIEW

Convolutional Neural Network (CNN) architectures were historically classified into four types: AlexNet [8], GoogleNet [9], ResNet50 [10], and another instance of GoogleNet. Each architecture incorporated an output layer, several hidden layers, and an input layer in distinct configurations [11]. These networks are utilized to perform the essential function of classifying CT scan images as benign or malignant. By harnessing the combined capabilities and architectures of these networks, this method is strategically applied to achieve highly effective image classification, leveraging the strengths of each network to secure precise diagnostic results.

AlexNet, a groundbreaking eight-layer convolutional neural network, consists of five types of layers: max-pooling, normalization, convolutional, and Rectified Linear Unit (ReLU) activation functions. Following these, the network features fully connected layers and dropout layers [12], which culminate in the creation of the softmax layer.

AlexNet's core strength is its autonomous capacity to identify distinctive features in input images and classify them accordingly. Initially intended to classify images into 1,000 different categories, this study has modified the AlexNet architecture for binary classification, effectively differentiating between malignant and benign characteristics. This adapted version of AlexNet demonstrates enhanced efficiency in image classification compared to traditional methods.

GoogleNet features a deep neural network with 22 hidden layers, enhancing its ability to classify samples more effectively. Like AlexNet, GoogleNet excels in automatically extracting features from input images and classifying them. Originally designed to categorize images into 1,000 different classes, this study has adapted GoogleNet for binary classification, specifically to differentiate between malignant and benign characteristics. This customized GoogleNet shows improved performance in image classification compared to existing methods.

ResNet50 advances neural network complexity with its 50 hidden layers, enhancing its capability for more efficient sample classification. Like its predecessors, ResNet50 is adept at autonomously extracting features from input images and classifying them. Initially designed to categorize images into 1,000 different classes, this study has reconfigured ResNet50 for binary classification, focusing on distinguishing malignant from benign characteristics. The adapted ResNet50 demonstrates superior efficacy in image classification compared to traditional methods [13].

VGG16, renowned for winning the 2014 ILSVR (ImageNet) competition, stands out as a pivotal model in computer vision due to its architectural simplicity and effectiveness. The architecture is characterized by consistent hyperparameters: it uses 3x3 convolutional filters with a stride of 1, and 2x2 max-pooling layers with a stride of 2, applied uniformly across the network. The design culminates in two fully connected (FC) layers topped with a softmax activation function in the output layer. The "16" in VGG16 denotes the 16 weighted layers that make up this influential model.

VGG16 processes an RGB image with dimensions of 224 by 224 pixels. It begins by calculating the mean RGB value from all the images in the training set and then subtracts this mean from each image to center the data. The architecture prominently features the repeated use of 3x3 convolutional filters throughout, maintaining a consistent and uniform convolutional operation. This meticulous design has solidified VGG16's status as a powerful and reliable CNN model for diverse image classification tasks [14].

IV. Critical Analysis

Author	**Comparison between different Lung Cancer Detection System**				
	Year	***Problem Statement***	***Dataset***	***Method***	***Accuracy***
[15]	2023	A Deep Learning Method for Lung Cancer Detection and Classification	CT Scan Images	ResNet-50	98%
[16]	2023	A Method for Detecting and Classifying Lung Cancer Using the AlexNet CNN Algorithm Model	LIDC-IDRI Dataset	Modified Alex Net Architecture	97.02 %
[17]	2022	Support Vector Machine and Modified AlexNet Architecture for the Detection of Lung Cancer	LUNA16 dataset	Lung Net SVM Model.	97.42 %
[18]	2021	Detection of Lung Cancer with the VGGNET-16 Architecture	CT Scan Images	VGG-16 and Resnet	97%
[19]	2020	CNN's Capability to Identify Lung Cancer from	Histopathological image	CNN	96.11 %

		the Histopathological Images	s		
[20]	2019	In-depth examination of the AlexNet and Google Net for the detection of lung cancer	LIDC-IDRI image dataset.	AlexNet and GoogLeNet	99.01%
[21]	2018	CT Scan Images for Identification of Lung Cancer	CT Scan Images	SVM	92%

SYNTHESIS AND IMPLICATIONS

Bansal developed a novel method to boost image classification performance by combining deep features from the VGG19 model with traditional techniques such as SIFT, SURF, ORB, and Shi-Tomasi corner detection. Their research showed that integrating these features with a Random Forest (RF) classifier resulted in a remarkable accuracy of 93.73%, highlighting the benefits of merging deep learning with classical approaches. [22].

Toğaçar introduced a deep learning model utilizing DarkNet-19 that amplified weak features and employed Support Vector Machines (SVM) for data classification. This method achieved exceptional outcomes, including an overall accuracy of 99.69%, an impressive AUC of 99.3%, and robust F-measure, precision, recall, and accuracy rates of 97.1%. Our technique successfully combines optimization strategies to accurately classify images [23].

Dritsas and Mesut proposed employing machine learning, specifically the rotation forest model, for early lung cancer detection in a separate case, demonstrating the versatility of machine learning techniques in healthcare environments.

Inception V3, an evolved CNN model for image classification, builds on the foundations of Inception V1 (GoogleNet) by incorporating multiple filters simultaneously, which helps prevent overfitting and enhances the model's robustness. While Inception V1 struggled with overfitting due to its deep convolutional layers, Inception V3 adopts parallel layer configurations rather than just depth to boost performance. It also significantly refines the dimension reduction approach of Inception V1, lowering computational demands by employing smaller convolutional layers instead of larger ones. Additionally, it enhances activation dimensions for improved outcomes by reducing grid sizes using techniques like max pooling and average pooling.

The VGG-19 model, an extension of the VGG series, includes 19 layers consisting of convolutional, max-pooling, and fully connected layers. It processes RGB images of 224 x 224 pixels size, and applies preprocessing by subtracting the mean RGB value from each pixel to normalize the data. This model preserves image resolution through the use of spatial padding and employs 3x3 convolutional kernels activated by ReLu functions. Max pooling is implemented using a 2x2 window with a stride of 2, facilitating dimension reduction while maintaining important features. The Rectified Linear Units (ReLu) enhance the model's non-linearity, improving both classification accuracy and processing efficiency. The architecture concludes with a softmax function across 1000 channels for categorizing images into 1000 classes as part of the ILSVRC challenge. Further details on the VGG-19 model and its capabilities in image classification are discussed in reference [24].

The study seeks to tackle the urgent requirement for improved early detection of lung cancer, given its significant global prevalence and high mortality rates. Although there have been advances in medical imaging and machine learning, there remains a vital need for effective and reliable models capable of analyzing CT images to identify lung cancer nodules at early stages [25]. The objective of the research is to address this gap by assessing the effectiveness of various deep learning models specifically for lung cancer detection, aiming to enhance diagnostic precision and outcomes for patients [26].

VI. Recommendations for Future Research

Talukder's composite ensemble model, utilizing the LC25000 dataset for lung cancer screening, reached an impressive 99.05% accuracy. This approach outperformed earlier models, highlighting the effectiveness of ensemble models combined with transfer learning in boosting diagnostic precision and their suitability for clinical use.

Phankokkruad's research demonstrated the success of ensemble models in identifying lung cancer, showing that while individual transfer learning models like VGG16, ResNet50V2, and DenseNet201 had varying accuracies, their collective use as an ensemble enhanced validation reliability to 91%. Additionally, Chen's hybrid framework, which combined Inception v3 with feature extraction modules to differentiate between lung cancer and healthy tissue in pathology images, surpassed similar studies. This framework showcased the effectiveness of hybrid deep learning models in accurately diagnosing cancer, achieving an impressive 99.60% accuracy [27].

VII. Conclusion

Research indicates that AlexNet outperforms GoogleNet in diagnosing respiratory malignancies using neural network analysis of medical images, achieving superior accuracy and other metrics. Concurrently, the ResNet architecture supports training of profoundly deep networks by utilizing innovative residual connections to combat the issue of vanishing gradients. Our approach to lung cancer diagnosis employs four deep learning models: AlexNet, Inception V1, ResNet-50, and VGG16. Evaluations of CT and histology images suggest that our method, which harnesses these models, holds significant promise for enhancing early detection. Plans are underway to further improve performance by integrating deep learning with optimization techniques such as fuzzy genetic algorithms. In conclusion, while AlexNet shows superior performance over GoogleNet, ResNet enables training of deeper networks. Utilizing these models in lung imaging is optimistic for early diagnosis, with potential enhancements through optimization.

VIII. References

[1] Hadrien T. Gayap and Moulay A. Akhloufi, "*Deep Machine Learning for Medical Diagnosis, Application to Lung Cancer Detection: A Review*",BioMedInformatics Jan 2024, https://doi.org/10.3390/biomedinformatics4010015.

[2] B. K. Hatuwal and H. C. Thapa, "Lung cancer detection using convolutional neural network on histopathological images," *International Journal of Computer Trends and Technology*, vol. 68, no.10,pp.21–24,Oct. 2020, doi: 10.14445/22312803/ijctt-v68i10p104.

[3] Arash Heidari, Danial Javaheri, Shiva Toumaj, NimaJafari Navimipour , Mahsa Rezaei, Mehmet Un al,*"A new lung cancer detection method based on the chest CT images using Federated Learning and blockchain systems", Elsevier Volume 141, July 2023, 102572,* https://doi.org/10.1016/j.artmed.2023.102572

[4] D. Riquelme and M. A. Akhloufi, "Deep learning for lung cancer nodules Detection and classification in CT scans," *AI*, vol. 1, no. 1, pp. 28–67, Jan. 2020, doi: 10.3390/ai1010003.

[5] B. Almas, K. Sathesh, and S. Rajasekaran, "A deep analysis of Google Net and AlexNet for lung cancer detection," *International Journal of Engineering and Advanced Technology*, vol. 9, no. 2, pp. 395–399, Dec. 2019, doi: 10.35940/ijeat.b3226.129219.

[6] S. T. M. Sheriff, J. V. Kumar, S. Vigneshwaran, A. Jones, and J. Anand, "Lung Cancer Detection using VGG NET 16 Architecture," *Journal of Physics*, vol. 2040, no. 1, p. 012001, Oct. 2021, doi: 10.1088/1742-6596/2040/1/012001.

[7] Wisdomml, "Understanding ReSNet-50 in depth: architecture, skip connections, and advantages over other networks -," *Wisdom ML*, Mar.30,2023.https://wisdomml.in/understanding-resnet-50-in-depth-architecture-skip-connections-and-advantages

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[9] C. Szegedy et al., "Going deeper with convolutions," 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA,USA, 2015,pp.1-9, doi: 10.1109/CVPR.2015.7298594.

[10] He, T., Zhang, Z., Zhang, H., Zhang, Z., Xie, J., Li, M. (2019). Bag of tricks for image classification with convolutional neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 558-567.

[11] Liu, Y.H. (2018). Feature extraction and image recognition with convolutional neural networks. Journal of Physics: Conference Series, 1087(6): 062032. https://doi.org/10.1088/1742-6596/1087/6/062032

[12] Yang, J., Yang, G. (2018). Modified convolutional neural network based on dropout and the stochastic gradient descent optimizer. Algorithms, 11(3): 28. https://doi.org/10.3390/a11030028

[13] T. Sajja, R. Devarapalli, and H. K. Kalluri, "Lung cancer detection based on CT scan images by using deep transfer learning," *Traitement Du Signal*, vol. 36, no. 4, pp. 339–344, Oct. 2019, doi: 10.18280/ts.360406.

[14] A. Mohite, "Lung Cancer Diagnosis using Transfer Learning," *International Journal of Scientific Research and Management*, vol. 9, no. 11, pp. 621–634, Nov. 2021, doi: 10.18535/ijsrm/v9i11.ec02.

[15] M. F. Khatun, M. R. Ajmain and M. Assaduzzaman, "A Deep Learning Approach to Detect and Classification of Lung Cancer," 2023 International Conference for Advancement in Technology (ICONAT), Goa, India, 2023, pp. 1-6, doi: 10.1109/ICONAT57137.2023.10080801.

[16] K. . B. C. and N. . K. B., "An Approach of AlexNet CNN Algorithm Model for Lung Cancer Detection and Classification", *IJRITCC*, vol. 11, no. 11s, pp. 49–54, Oct. 2023.

[17] Naseer, T. Masood, S. Akram, A. Jaffar, M. Rashid *et al.*, "Lung cancer detection using modified alexnet architecture and support vector machine," *Computers, Materials & Continua*, vol. 74, no.1, pp. 2039–2054, 2023.

[18] S. T. M. Sheriff, J. V. Kumar, S. Vigneshwaran, A. Jones, and J. Anand, "Lung Cancer Detection using VGG NET 16 Architecture," *Journal of Physics*, vol. 2040, no. 1, p. 012001, Oct. 2021, doi: 10.1088/1742-6596/2040/1/012001.

[19] B. K. Hatuwal and H. C. Thapa, "Lung cancer detection using convolutional neural network on histopathological images," *International Journal of Computer Trends and Technology*, vol. 68, no.10,pp.21–24,Oct.2020, doi: 10.14445/22312803/ijctt-v68i10p104.

[20] B.Almas, K.SatheshandS.Rajasekaran, "A Deep Analysis of Google Net and AlexNet for Lung Cancer Detection", International Journal of Engineering and Advanced Technology (IJEAT), vol. 9, no. 2, pp. 395–399, Dec. 2019, doi: 10.35940/ijeat.B3226.129219.

[21] S. Makaju, P. W. C. Prasad, A. Alsadoon, A. K. Singh, and A. Elchouemi, "Lung Cancer Detection using CT Scan Images," *Procedia Computer Science*, vol. 125, pp. 107–114, Jan. 2018, doi: 10.1016/j.procs.2017.12.016.

[22] M. Bansal, M. Kumar, M. Sachdeva, and A. Mittal, "Transfer learning for image classification using VGG19: Caltech-101 image data set," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 4, pp. 3609–3620, 2023.

[23] M. Toğaçar, "Disease type detection in lung and colon cancer images using the complement approach of inefficient sets," *Computers in Biology and Medicine*, vol. 137, Article ID 104827, 2021.

[24] V. Rajasekar, M. Vaishnnave, S. Premkumar, S. Velliangiri, and V. Rangaraaj, "Lung cancer disease prediction with CT scan and histopathological images feature analysis using deep learning

techniques," *Results in Engineering*, vol. 18, p. 101111, Jun. 2023, doi: 10.1016/j.rineng.2023.101111.

[25] Manish Madhava Tripathi, Saurabh Pandey, "Diagnosis of Diabetes using Artificial Intelligence Techniques by using Bio Medical Signal Data", International Journal of Research and Development in Applied Science and Engineering (IJRDASE) ISSN-2454-6844, Volume 13, Issue 2, May 2017

[26] Tripathi, M. M., Haroon, M., Khan, Z., & Husain, M. S. (2022). Security in digital healthcare system. Pervasive Healthcare: A Compendium of Critical Factors for Success, 217-231.

[27] M. A. Talukder, M. M. Islam, M. A. Uddin, A. Akhter, K. F. Hasan, and M. A. Moni, "Machine learning-based lung and colon cancer detection using deep feature extraction and ensemble learning," *Expert Systems with Applications*, vol. 205, Article ID 117695, 2022.