Lung Cancer Detection and Classification using Transfer Learning with Pre-trained VGG19 Convolutional Neural Networks

Surajit Das
Department of AI&DS
B V Raju Institute of Technology
Narsapur, Telangana, India Pin: 502313
0000-0003-2015-7251

Lavanya G
Department of AI&DS
B V Raju Institute of Technology
Narsapur, Telangana, India Pin: 502313
0009-0005-4930-6056

Sangem Jaya Prakash
Department of AI&DS
B V Raju Institute of Technology
Narsapur, Telangana, India Pin: 502313
0009-0002-8233-7055

Niladri Sekhar Dey
Department of AI&DS
B V Raju Institute of Technology
Narsapur, Telangana, India Pin: 502313
0000-0003-2880-6500

Jeshwanth Panuganti
Department of AI&DS
B V Raju Institute of Technology
Narsapur, Telangana, India Pin: 502313
0009-0009-1007-0583

Rokati Poojitha
Department of AI&DS
B V Raju Institute of Technology
Narsapur, Telangana, India Pin: 502313
0009-0003-1890-4489

***Abstract*—It is possible to diagnose and identify a variety of illnesses with the use of high-quality figures obtained from medical equipment. However, obtaining and storing these kinds of photos may be quite costly, and diagnosing a patient might take a long time. Artificial intelligence (AI) solutions for automatic diagnosis may play a major role in addressing the challenges of time and cost. The categorization of medical images may be effectively solved by pre-trained deep learning models. Lung cancer continues to be a widespread and serious type of cancer on a global scale. Timely and precise identification is crucial for successful treatment and enhanced patient results. This study presents a novel approach to the identification and categorization of lung cancer by using transfer learning via a VGG19 Convolutional Neural Network (CNN) that has been trained beforehand. Our work harnesses the power of transfer learning by leveraging the VGG19 architecture, provides the basis for lung cancer diagnosis, having been pre-trained on a large dataset. Our carefully curated dataset encompasses over 14600 diverse lung images, covering benign, malignant, and normal cases, providing the model with a rich source of information. The model demonstrated outstanding performance metrics, achieving a training accuracy of 99.68%, 98.11% for validation accuracy and 97.93% for test accuracy. Such high accuracy holds great promise for expediting and improving the diagnostic capabilities of healthcare professionals. By leveraging Transfer Learning from VGG19, our model demonstrates adaptability to diverse medical imaging tasks, making it a valuable tool for real-world clinical applications.**

***Index Terms*—Convolutional Neural Network, VGG19, Lung Cancer, Transfer Learning**

I. Introduction

Lung cancer persists as one of the most lethal and widespread types of cancer globally [1], necessitating the development of advanced diagnostic tools to combat its devastating impact [2]. By enabling timely intervention and treatment, early detection of lung cancer is essential for improving outcomes for patients [3], [4]. Medical imaging, particularly chest X-rays and CT scans, serves as a primary modality for diagnosing lung cancer [5]. However, the accurate and efficient analysis of these images is a complex and challenging task. Tumours mostly come in two varieties. It may be benign or cancerous. The term "malignant" refers to cancerous tumours. It has the ability to proliferate throughout the body. However, benign tumours do not have malignant properties. They either develop slowly or not at all, or they do [6]. The majority of the time, after a doctor removes them, they remain gone. A benign lung tumor makes about 95% of the total [2]. However, it may potentially be cancerous [7]. By combining the techniques of [8] and [9], using deep learning neural networks for image processing, we have made it possible to diagnose cancer quickly and affordably, which is advantageous for both patients and healthcare professionals. This synergy offers a promising avenue for significant advancements in the field of cancer detection. In this regard, combining deep learning with CNNs has shown to be a viable method for improving the precision and speed of lung cancer identification and categorization [9]. This work offers a novel method for classifying and detecting lung cancer, employing Transfer Learning with the pre-trained VGG19 CNN architecture. Transfer Learning [10] leverages the knowledge acquired by a CNN on a vast dataset and adapts it to a specific task, in this case, the identification of lung cancer from medical images [11]. Our research revolves around the utilization of the highly acclaimed VGG19 model, renowned for its exceptional capabilities in image recognition, as a cornerstone. Through the leverage of VGG19's capabilities, our goal is to revolutionize the way that lung cancer is detected and treated. This research contributes to the broader field of medical

imaging and underscores the significance of leveraging pre-trained CNNs in real-world clinical applications. The implications of this work are profound, as it promises to expedite lung cancer diagnosis, enhanced outcomes for patients, and lessen the workload of this deadly disease on society. By embracing Transfer Learning with VGG19, we aim to pave the way for more accurate, efficient, and accessible lung cancer detection methods, ultimately enhancing healthcare delivery and saving lives. An overview of the structure of this document is provided below: Section II explores current state-of-the-art Related Work. Part III provides a detailed rundown of the recommended approach. The findings from our tests are shown in Section IV. Our discussion are presented in Section V. Lastly, Section VI encapsulates our conclusions and outlines future avenues for research.

II. Related Work

Over the past few decades, deep learning models have seen extensive utilization in the field of cancer detection [12]–[14]. Lung cancer diagnosis requires the presence of both solid and pulmonary nodules, which are masses of tissue around the lungs [15]. Depending on the type of cells, the nodules found in the lungs can either be benign or malignant [16]. In a study conducted by Song et al. [17], they compared the CNN and deep learning models for detecting lung tumors. They noted that CNN did better than the stacked auto-encoder and DL models when it came to performing lung tumor detection. He et al. [18] proposed ResNets, which employ skip connections to facilitate the training of exceedingly deep networks. Their research demonstrated impressive performance gains in image recognition tasks, inspiring subsequent studies to adopt ResNets as a foundation for lung cancer detection models. Another influential architecture in the field of deep learning is the VGG network, introduced by Simonyan et al. [10], VGG networks are characterized by their simplicity and uniform architecture, comprising multiple convolutional layers and max-pooling layers. These networks have shown remarkable capabilities in image recognition tasks, making them a compelling choice for lung cancer classification. Additionally, Esteva et al. [9] provide an example of the effective use of deep learning to medical picture interpretation. Their work focused on dermatologist-level classification of skin cancer, showcasing the potential of CNNs to outperform human experts in diagnosing medical conditions. The present study provides a compelling baseline for the use of deep learning to the diagnosis of lung cancer. In the context of lung cancer, numerous researchers have explored the utilization of deep learning techniques, including CNNs, to extract meaningful features from radiological images. However, their paper distinguishes itself by employing Transfer Learning with the pre-trained VGG19 CNN architecture, capitalizing on its proven effectiveness in image recognition tasks. This approach aligns with the broader trend of adapting state-of-the-art CNN architectures for specific medical imaging tasks. In a study conducted on lung tumor detection, Song et al. [16] conducted a comparative analysis of the performance of CNN, stacked auto-encoders, and deep learning models. The researchers discovered that the CNN model had superior performance compared to both the DL and stacked models. Before CNN's training, Yu et al. [19] developed a system that would perform lung segmentation and bone exclusion. The system was developed by Shakeel et al. [20], who used pre-processed images. After carrying out denoising procedures, the AI neural network was trained to identify lung cancer. The four-part system proposed by Ardila et al. [21] included segmentation, cancer risk assessment, full-volume analysis, and ROI identification. After analyzing lung segmentation, ROI identification predicts the maximum region of nodules, while the cancer risk assessment prepares for the likelihood of cancer. By building upon the foundations laid by VGG networks, and previous successes in medical image analysis, our research contributes to the growing body of knowledge aimed at advancing lung cancer detection and classification. The suggested technique provides healthcare practitioners with a potent tool to boost diagnosis accuracy and consequently improve patient outcomes.

III. Methodology

In this study, a deep learning training model employing histopathological lung cancer tissue images is used to develop an automated system with the capability of identifying lung cancer. Conventional methods of lung cancer detection are quite expensive and time-consuming. We provide the suggested methods in this section.

A. *Dataset Collection and Preprocessing*

This study employs the "Lung Cancer Dataset" obtained from Kaggle [22] to construct and assess a comprehensive framework designed for the analysis of images related to lung cancer. Three classifications have been applied to the photos of lung cancer in this dataset: "Normal," "Benign," and "Malignant." These images serve as the cornerstone of our investigation, constituting a meticulously curated collection of over 1000 lung images spanning these three distinct categories.

In its original form, the dataset featured around 120 "Normal" images, 416 "Benign" lung images, and 561 "Malignant" images. It is worth highlighting that this dataset consists of gray scale images with varying dimensions, thereby introducing a unique analytical challenge. A visual representation of the image distribution is presented in Fig. 1 for reference.

The application of data augmentation techniques led to a well-balanced distribution in the dataset, comprising 4160 instances of "Normal cases," 5640 instances of "Malignant cases," and 5019 instances of "Benign cases." Employing methods such as rotation, shifts, and flipping, we introduced diversity while preserving the integrity of the images. This effectively mitigated class imbalance and bolstered the resilience of our models. As illustrated in Fig.2, we present a representative sample of an augmented image generated from the dataset. This augmented dataset served as the foundational dataset for our lung cancer image analysis framework, enabling the

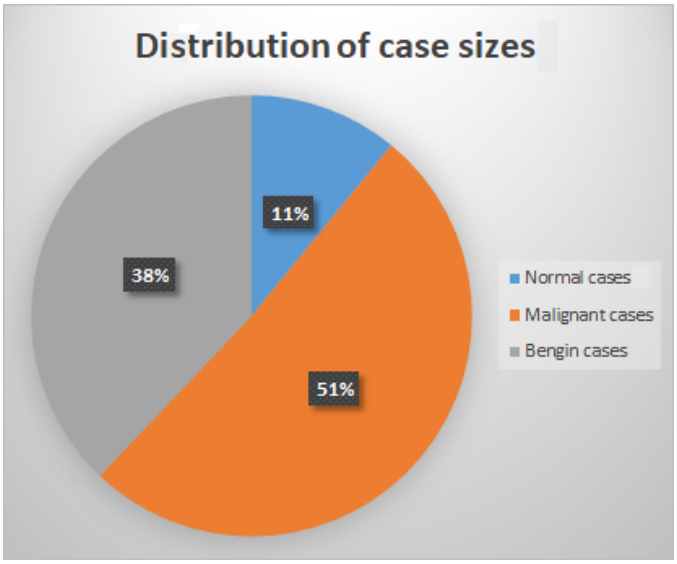

Fig. 1. Distribution of Images

development of models proficient in handling real-world data complexities.

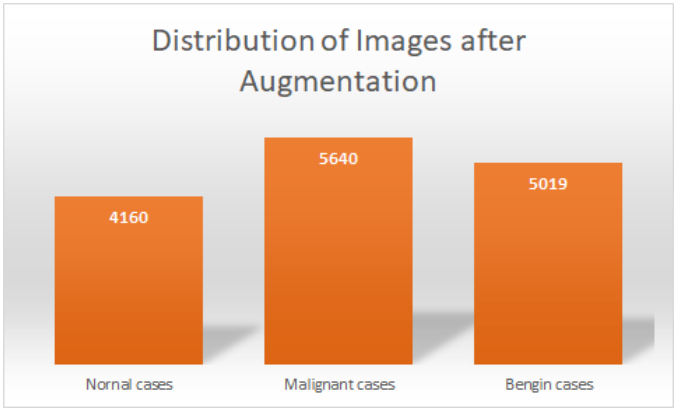

Fig. 2. Distribution of Images after augmentation

Additionally, normalization techniques were applied to scale a set of values to a consistent range, typically within the interval [0, 1]. This process was executed individually for each value, such as pixel values within images. The equation for normalization is:

$$\text{Normalized Value } (x_{\text{norm}}) = \frac{x - \text{min\_val}}{\text{max\_val} - \text{min\_val}} \quad (1)$$

Where:

x : Original value of the data point.

min_val : Minimum value of that feature across all data points.

max_val : Maximum value of that feature across all data points.

B. *Transfer Learning with VGG19*

In this methodology, we present the step-by-step process for implementing a lung cancer detection and classification system using transfer learning with the VGG19 CNN architecture [10], [11]. The approach begins with dataset preparation, where a dataset containing lung tissue images categorized into ”Bengin cases,” ”Malignant cases,” and ”Normal cases” is acquired and split into training, validation, and test sets. Next, we select the VGG19 model as the pre-trained CNN base, removing its classification layers to retain the convolutional feature extraction capabilities. We construct a custom classification head, comprising multiple dense layers with ReLU activation functions, Batch Normalization layers for convergence, and dropout layers to mitigate overfitting. The output layer consists of three neurons representing the three classes. Data preprocessing involves rescaling pixel values and resizing images to match the VGG19 input size. Stochastic gradient descent (SGD) optimization and categorical cross-entropy loss are equipped in the model, and various evaluation metrics. Finally, the model is trained using class weights, evaluated on the test dataset, and saved for future use or deployment, resulting in a robust lung cancer detection and classification system with high accuracy and performance. Fig. 3 shows the architecture that has been proposed for the VGG19 model.

C. *Performance Metrics*

In neural networks, performance metrics are used to evaluate a neural network model's performance on a specific task, such as classification. These metrics include numerical representations of the model's recall, accuracy, precision, F1-score, and other attributes [23]–[26]. Below, explain some common performance metrics used in neural networks along with their equations:

$$\text{Precision(A)} = \frac{\text{B}}{\text{B} + \text{C}} \quad (2)$$

$$\text{Recall(X)} = \frac{\text{B}}{\text{B} + \text{D}} \quad (3)$$

$$\text{F1-Score(Y)} = \frac{2 \cdot \text{A} \cdot \text{X}}{\text{A} + \text{X}} \quad (4)$$

$$\text{Specificity(Z)} = \frac{\text{E}}{\text{E} + \text{C}} \quad (5)$$

In the context of classification metrics:

True Positives (B): The number of positively anticipated cases that come true as projected. True Negatives (E): The number of accurately anticipated negative cases. False Positives (C): The number of positively predicted cases that were not as expected. False Negatives (D): The number of negatively anticipated occurrences that were not as expected.

IV. Experimental Results

Our thorough evaluation of the Transfer Learning model for Lung Cancer Detection and Classification produced highly promising results. Utilizing a meticulously curated and diverse dataset, our VGG19 model demonstrated its effectiveness in both detecting and classifying lung cancer. The models were

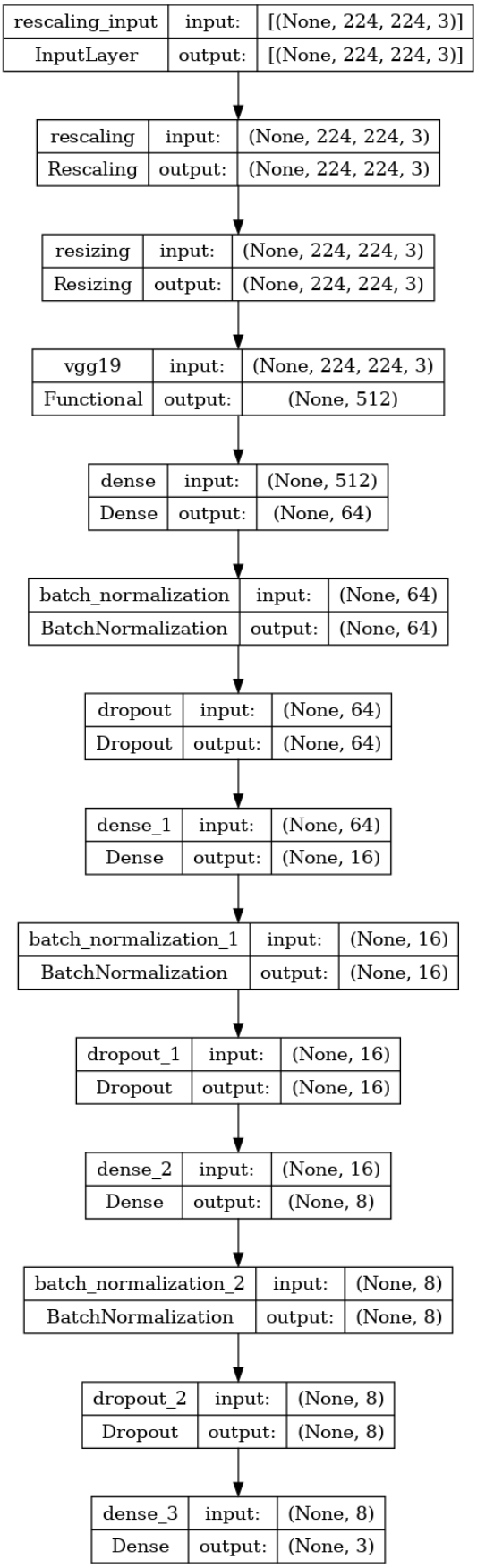

Fig. 3. The proposed VGG19 model architecture

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 224, 224, 3)	0
resizing (Resizing)	(None, 224, 224, 3)	0
vgg19 (Functional)	(None, 512)	20024384
dense (Dense)	(None, 64)	32832
batch_normalization (BatchNormalization)	(None, 64)	256
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 16)	1040
batch_normalization_1 (BatchNormalization)	(None, 16)	64
dropout_1 (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 8)	136
batch_normalization_2 (BatchNormalization)	(None, 8)	32
dropout_2 (Dropout)	(None, 8)	0
dense_3 (Dense)	(None, 3)	27

Total params: 20,058,771
Trainable params: 20,058,595
Non-trainable params: 176

Fig. 4. The summary of the layers of the VGG19 model

implemented in Python within a Google Colab environment, benefiting from a P100 GPU and 16 GB of RAM.

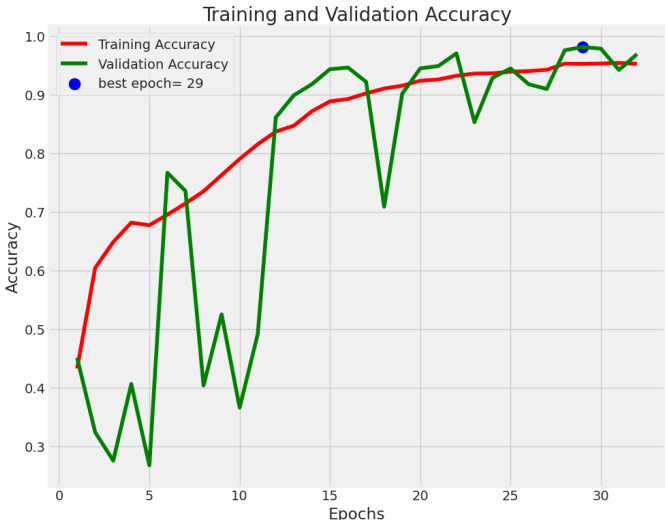

Fig. 5. Training and validation accuracy curves for VGG19.

In Fig.4, we shown the summary of the layer of the VGG19 model and Fig.5, we present the training and validation results of VGG19. The orange line depicts the training accuracy, steadily increasing to 99% after 27 epochs. Meanwhile, the green curve illustrates the validation accuracy, starting at 45.56% and reaching 99.03% after 30 epochs. The training process concluded at epoch 32, following three learning rate adjustments, as the learning curve began to exhibit signs of overfitting with minimal improvement. In total, the training

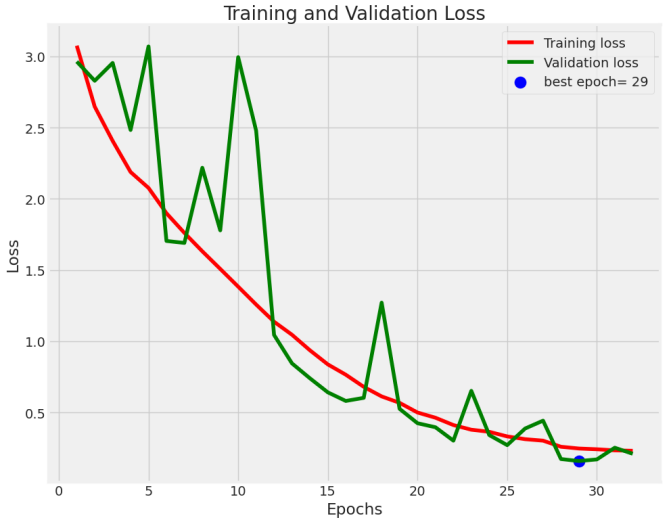

Fig. 6. Training and validation loss curves for VGG19.

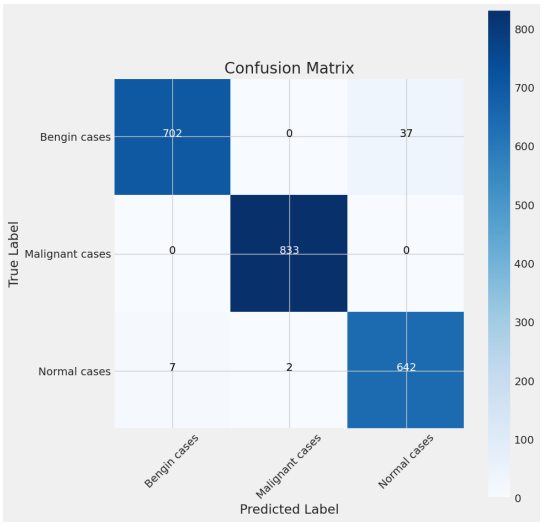

Fig. 7. Confusion Matrix

process took 1 hour, 50 minutes, and 43.75 seconds. To get the best possible balance between training and validation accuracy, we adjusted the number of training epochs. The loss curves for the VGG19 model, depicted in Fig. 6, illustrate exceptional learning performance with minimal errors, as evidenced by an almost 0.1 score. With increasing epochs, both training and validation losses consistently decreased. The validation loss started at 3.0 and reduced to 0.2, while the training loss reached 0.01 after 29 epochs. In TABLE I, we present the Precision, Recall, F1-score, and Support metrics for the VGG19 model, which evaluate its performance on the dataset. Across all classes (Bengin, Malignant, and Normal cases), the average F1-score, Precision, and Recall achieved 98%, along with weighted and macro-averages.

Fig. 7 displays the Confusion Matrix generated by the VGG19 model. Blocks with dark purple hues indicate the accuracy of categorization. The matrix displays 702, 833, and 642 true positives for each of the three tumour classes—Bengin cases, Malignant cases, and Normal cases—respectively. With extremely few classification mistakes, it has a classification accuracy of average 0.98 or ”98%” for Bengin cases, ”Malignant cases,” and ”Normal cases”. In Fig. 8 shown the results of Train, Validation and Test Loss and accuracy Graphs of VGG19.

TABLE I
CLASSIFICATION REPORT

	Precision	Recall	f1-score	Support
Bengin cases	0.99	0.95	0.97	739
Malignant cases	1.00	1.00	1.00	833
Normal cases	0.95	0.99	0.97	651
accuracy			0.98	2223
macro avg	0.98	0.98	0.98	2223
weighted avg	0.98	0.98	0.98	2223

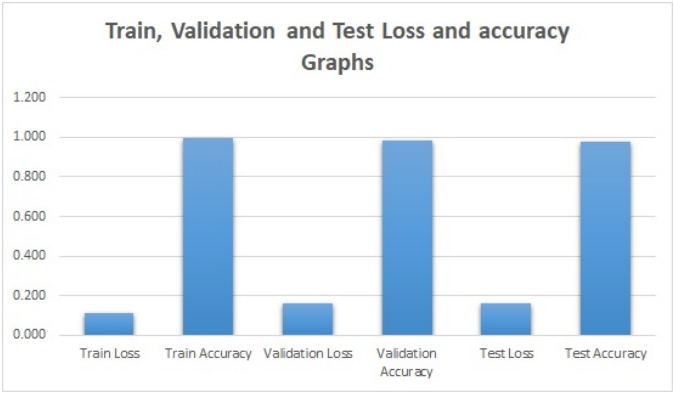

Fig. 8. Train, Validation and Test Loss and accuracy Graphs

V. DISCUSSION

The exceptional performance of our model is a promising step towards accurate and efficient lung cancer detection. Achieving a test accuracy of 97.93% showcases the potential for clinical implementation. The model's ability to classify lung scans with high precision and recall, even in cases of class imbalance, underlines its practicality and reliability. According to TABLE II, the suggested obtained has a higher average test accuracy value of 97.93 than all current works. Furthermore, the suggested method's average precision is 98, which is greater than the average precision of all current works. The suggested technique produced an average recall value of 95.89, which is greater than all previous efforts. As a consequence of TABLE II, it is inferred that the suggested strategy outperforms previous current studies.

VI. CONCLUSION

In our study, we harnessed the power of Transfer Learning using the VGG19 CNN to enhance Lung Cancer Detection and Classification, achieving a remarkable test accuracy of 97.93%. This approach efficiently leveraged pre-trained

TABLE II
COMPARISON OF LUNG CANCER DETECTION RESULTS

Existing works	**Average Test Accuracy (%)**	**Average Precision (%)**	**Average Recall (%)**
A. Asuntha et al. [31]	94.97	96.68	95.89
Suren et al. [28]	92.2	93.5	91.3
Orozco HM et al. [30]	95.66	96.15	97.32
Taruna et al. [29]	97.12	97.14	96.33
Our Model (This Study)	97.93	98	98

VGG19 weights, expediting training and enabling the model to grasp critical nuances in lung cancer identification. Importantly, this methodology has broader applicability in medical imaging, addressing data scarcity challenges. Our model's potential in clinical workflows is promising, offering radiologists an invaluable tool for more efficient lung cancer screening and diagnosis. However, we acknowledge certain limitations. While our dataset is extensive, it may not encompass all scenarios, necessitating validation on external datasets and in clinical trials. In conclusion, our research represents a significant advancement in applying deep learning to medical imaging, particularly in lung cancer diagnosis. With further refinement and validation, our model has the potential to expedite early diagnosis and enhance patient outcomes in the fight against lung cancer.

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