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Mmt-Vin: An Intelligent Lung Cancer Detection Framework Utilizing Machine Learning

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Lung cancer, one of the top causes of cancer-related deaths, relies on early detection for effective treatment. We suggest an automated system that leverages machine learning to analyze CT scans, assisting radiologists in accurately detecting suspicious lung nodules. The approach involves pre-processing CT images to highlight nodule features. Machine learning models, such as CNNs, are trained on annotated CT scans to recognize patterns of malignant and benign nodules. Different CNN architectures, including ResNet, DarkNet, and EfficientNet, are evaluated to determine the most efficient model for detection. We introduce a model called MMT-VIN, which is built upon the VGG-19 approach. The proposed lung cancer detection method achieves an accuracy of approximately 98.8%, outperforming the methods it was compared against.

Keywords: Lung cancer detection, CT images, machine learning, CNN architectures.

1. Introduction: Lung cancer remains the top cause of cancer deaths worldwide. Smoking, secondhand smoke, alcohol, radon gas, asbestos, other toxins, radiation therapy, and family history of lung cancer are all risk factors [1]. Early lung cancer identification can significantly improve survival rates. For lung cancer detection, researchers use image processing, machine learning, or hybrid methods from the literature. Support Vector Machines (SVM), Naive Bayes (NB), Decision Tree (DT), Back Propagation Network (BPN), K-Nearest Neighbor (KNN), Logistic Regression (LR) [2], and Convolutional Neural Network (CNN). CNNs are popular because local receptive fields and pooling layers reduce the number of parameters compared to other neural networks. They eliminate manual nodule signifiers and reduce false positives [3].

The most frequent imaging diagnostic method, chest radiography (CXR), can be used to diagnose chest disorders such lung cancer, TB, pneumonia, pneumoconiosis, and emphysema. It is the most widely used, least radioactive, and affordable diagnostic method that can identify unidentified pathological alterations [4]. On comparing with computed radiography (CR), computed tomography (CT) has high sensitivity and also an early lung cancer diagnosis is largely influenced by early CT screening [5]. In order to predict the kind of lung cancer using

CT images, a deep learning method was presented in [6]. This model classifies malignant tumors using densely connected convolutional networks (DenseNet) and aggregates classification results for improved performance using adaptive boosting (adaboost). DenseNet model outperformed DenseNet without adaboost, VGG16, AlexNet, and ResNet with 89.95% accuracy.

In another study, the authors of [7] introduced a model named DFD-Net ("denoising first" two-path convolutional neural network) which comprises of denoising and detection part. Initially DR-Net (a residual learning denoising) model is used for removing the noise in pre-processing phase. After that for detecting lung cancer, denoised images produced by DR-Net model are given to a two-path convolutional neural network. For improving the performance of this model, discriminant correlation analysis is used which add more representative features and it is different from the conventional feature concatenation approach where two sets of features of different CNN layers directly concatenated. At last, to remove difficulties related with the image labels imbalance, a retraining technique is proposed. A superior CT scan lung nodule detection CAD method was presented in another work [8]. This method segments CT scan lung nodules using a fuzzy-based algorithm. Fuzzy soft membership functions automate segmentation. Fuzzy neural classifiers accurately categorize lung nodules as cancerous or benign. Many VGG16-T neural networks are trained with boosting technique, and [9] presented a weak classifier. Combining weak classifier VGG16-T networks improves accuracy.

2. Literature Review: Machine learning algorithms are increasingly transforming healthcare diagnostics by enabling faster and more accurate analysis of medical data. These algorithms can identify patterns and anomalies in large datasets, assisting clinicians in making informed decisions [10]. Applications include early detection of diseases, personalized treatment plans, and predictive analytics for patient outcomes. By leveraging machine learning, healthcare systems can enhance diagnostic accuracy and improve patient care efficiency [11]. Researchers have used machine learning and deep learning for categorization and prediction across imaging and signal modalities. Medical diagnostic systems increasingly use machine learning algorithms for lung disease prediction [12]. DarkNet-19, a deep learning model, uses YOLO object detection [13]. Five pooling layers and 19 convolutional layers make up DarkNet-19. Similar to VGG models, the DarkNet-19 model employs 3x3 filters following convolutional layers, but with twice as many channels. Additionally, batch normalization is used by the DarkNet-19 model to hasten convergence, steady the training procedure, and simplify model operation. Another study[14] suggested the DarkNet-19 model, one of the deep learning models, was used to train the picture classes from scratch. Selecting the ineffective characteristics in the feature set obtained from the DarkNet-19 model was done by utilizing the optimization techniques of Manta Ray Foraging and Equilibrium. The inefficient features were separated from the remaining features in the set, resulting in an efficient Complementary rule insets are a feature set. The effective characteristics that the two employed Combining optimization methods with the Support Vector Machine (SVM) for classification method.

The authors of [17] investigate the EfficientNet model, which employs a method called compound scaling to adjust all dimensions. A multiobjective architectural search optimizes FLOPs and accuracy in this method. For optimization, EfficientNet uses a search space and ACC (m) × [FLOPS (m)/T]w metric. ACC (m) and FLOPS (m) are the accuracy and FLOPs of model "m," while T and w are the desired FLOPs and hyperparameters. These factors are critical to balancing accuracy with computing efficiency. Multiple convolutional layers with different-sized kernels make up this network. The first input frame, with three color channels (red, green, blue), is 224 × 224 × 3. As layers unfold, resolution decreases to compress feature maps and width increases to improve accuracy. This technique collects key input frame features. In the second layer, kernels are 112 pixels wide, and in the next convolutional layer, they are 64 pixels wide. The last layer uses a maximum of 2,560 kernels, with a reduced resolution of 7 × 7, to capture the most prominent features. Max pooling, encoding, and SoftMax layers are added for classification.

Google introduced the EfficientNet[18], a group of convolutional neural networks (CNNs) created through an automated process of searching for neural network architectures. This automated approach streamlines the design of CNNs, resulting in models that exhibit enhanced performance while requiring fewer computational resources. The EfficientNet family encompasses various models, labeled as EfficientNet b0 through b7, each tailored to operate optimally with specific image dimensions to achieve a balance between performance and efficiency. In this investigation, EfficientNet b3 was selected as it possesses a comparable input size to that of the InceptionResNetV2 model.

A computer-aided detection (CADe) approach to detect lung nodules early in low-dose computed tomography (LDCT) images is proposed by [20]. This proposed approach begins with data preprocessing to improve low-dose image contrast. Exploring deep learning architectures like Alex, VGG16, and VGG19 yields concise features.

The suggested approach in [21] introduces a non-intrusive diagnostic method suitable for effective clinical evaluation. The proposed model demonstrates a reduction in parameter count, notably smaller than that of contemporary models. Additionally, we assessed the robustness of the dataset based on its scale. The suggested architecture's efficiency was measured using standard performance criteria. All transfer learning methods perform well on the dataset, including VGG 16, VGG 19, and Xception utilizing a 20-epoch structure. Preprocessing helps develop a credible model and speed up model integration, enabling future scenario prediction. By the 20th epoch, VGG 16 has 98.83, VGG 19 has 98.05, and Xception, has 97.4 percent accuracy. Goram Mufarah M. Alshmrani et al. [22] used a pre-trained VGG19 model, three CNN blocks for feature extraction, and a fully connected network for classification.

Table 2.1: Comparative Study of Various Algorithms

Authors	**Objective**	**Proposed Methodology**	**Gap Identified**	**Performance**

J. Redmon et al [13]	Introduce DarkNet-19 model for object detection	Build DarkNet-19 architecture for object detection using convolutional layers and pooling layers	Efficient object detection	DarkNet-19 achieves efficient object detection
M. Toğaçar [14]	Train DarkNet-19 for image classification	Use optimization techniques to select effective features from DarkNet-19 model, combine with SVM for classification	Optimize feature set and classification	Achieve effective image classification with DarkNet-19
Rachel Grossman et al [15]	Develop EfficientNet for brain metastases classification	Introduce noninvasive deep learning model (EfficientNet) for classifying brain metastases from NSCLC and SCLC	Enhance diagnostic tool for brain metastases	EfficientNet achieves sensitive and specific classification
H. Yang et al [16]	Optimize EfficientNet networks for accuracy and efficiency	Employ compound scaling and automated architectural search to optimize EfficientNet networks for ImageNet classification	Improve performance with less FLOPs	EfficientNet achieves state-of-the-art accuracy with fewer FLOPs
K. Muhammad et al [17]	Investigate EfficientNet model and compound scaling	Explore compound scaling to adjust dimensions of EfficientNet model, optimize accuracy and FLOPs balance	Optimize accuracy and computational efficiency	EfficientNet models achieve enhanced performance with efficiency balance
A. Lang et al. [18]	Introduce Google's EfficientNet CNN models	Employ automated process to design CNN models	Achieve improved performance	EfficientNet models optimize performance

		(EfficientNet) with enhanced performance and lower computational resources	with fewer resources	with resource efficiency
Various Authors [19]	Combine DCNN (VGG-19) and LSTMs for disease detection	Use VGG-19 and LSTMs to detect and classify NSCLC.	Improve disease detection and categorization	Achieve rapid and accurate detection and classification of NSCLC
A. Elnakib et al. [20]	Create CADe lung nodule detecting method	Enhance low-dose CT images, extract deep learning features, combine VGG19 with SVM classifier for lung nodule detection	Improve early lung nodule detection	Attain high detection accuracy and sensitivity in lung nodule detection
M. Humayun et al. [21]	Propose robust diagnostic method for clinical evaluation	Explore transfer learning techniques with VGG 16, VGG 19, and Xception, assess robustness and performance metrics	Enhance clinical evaluation and prediction	Achieve strong performance in clinical evaluation
Goram Mufarah M. Alshmrani et al. [22]	Use VGG19 and CNN for classification	Combine VGG19 and CNN for lung nodule classification, outperform existing methods	Achieve accurate diagnosis and treatment	Attain superior accuracy in lung nodule classification

Inspired by ongoing research efforts, this paper seeks to develop a reliable algorithm for lung cancer diagnosis that offers enhanced sensitivity and specificity while maintaining low time complexity. The next section outlines the proposed method and provides details of the work.

3. Proposed Methodology: The proposed lung cancer detection method is structured in multiple phases, with each phase explained sequentially. First, the overall workflow of the process is introduced.

3.1. Overview of the proposed approach: Multiple steps are required to classify lung cancer using a CNN with the MMT-Vin based on VGG-19 architecture. They include dataset gathering, image pre-processing, model training, and more. Figures 1 and 2 briefly describe the proposed methodology.

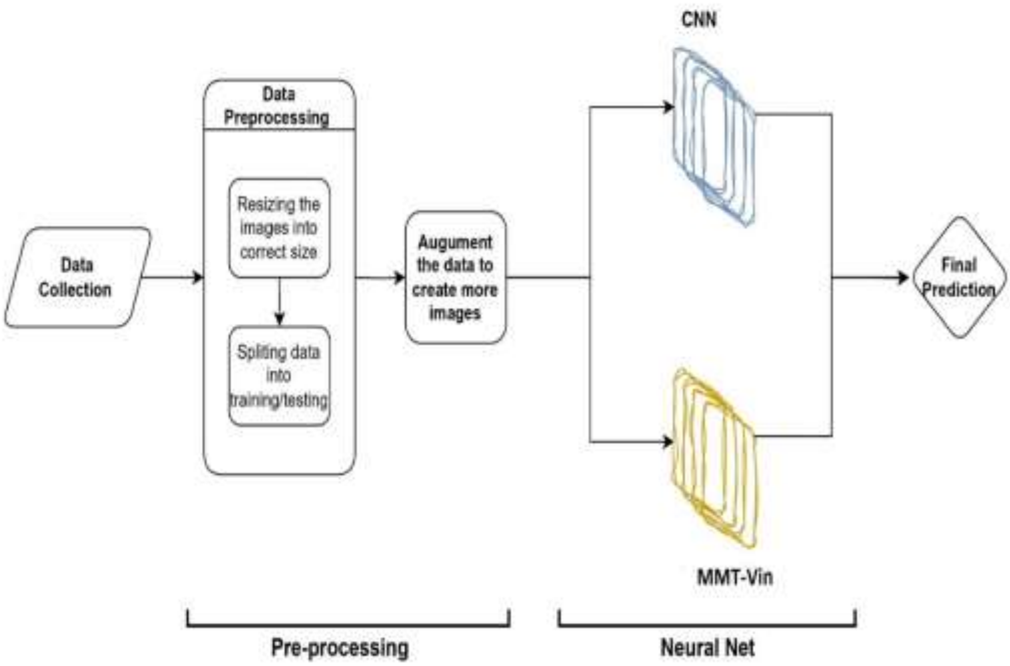
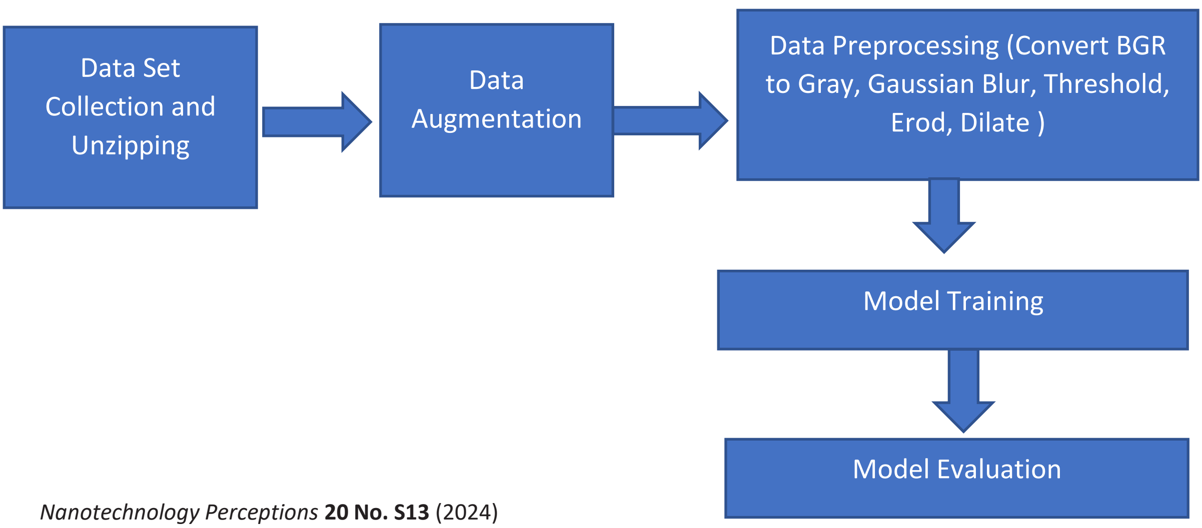


Fig. 3.1.1: Proposed MMT-Vin model



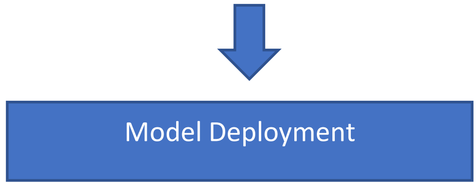
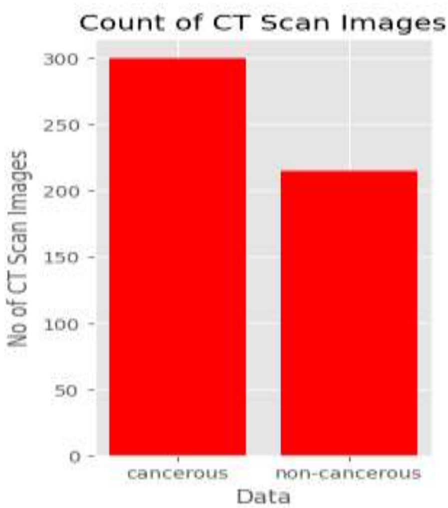


Fig. 3.1.2: Steps in Proposed MMT-Vin model

3.2 Dataset Collection: This section presents a comprehensive dataset of lung cancer images, which includes both malignant and benign cases. For the CNN model to learn effectively, it is essential that the dataset is diverse and accurately labeled. The lung cancer histopathology images were sourced from Kaggle during the data collection phase of this research. After unzipping we found the collection features a total of five hundred fifteen images of lung cancer. Now after augmentation we found more than four thousand images.



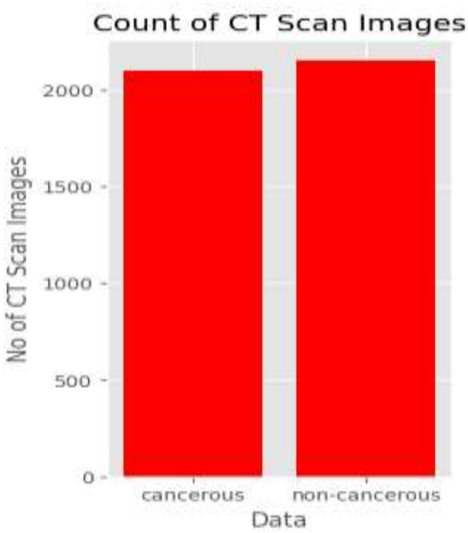


Fig. 3.2.1: Graph plot before Augmentation

Fig. 3.2.1: Graph plot after Augmentation

3.3 Data Pre-processing: Firstly, we convert images from BGR (Blue, Green, Red) to grayscale. The conversion uses specific weights for each channel to produce a single intensity value for each pixel. The formula often used is:
gray=0.299×R+0.587×G+0.114×B

By using below code we apply BGR to grayscale on our dataset-
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
We then apply Gaussian blur. Gaussian blur is a popular image processing technique that decreases noise and detail. Using a Gaussian function to average pixel values creates a smooth look. This approach blurs backgrounds and reduces high-frequency noise well.

By using below code we apply Gaussian Blur method on our dataset-**gray = cv2.GaussianBlur(gray, (5,5), 0)**

Also, we set some threshold value as shown below;

thres = cv2.threshold(gray, 45, 255, cv2.THRESH_BINARY)

It creates binary images from grayscale photographs by cutting off a specified intensity level. Pixels with values above the threshold are converted to one color (usually white), while those below are set to another (usually black). This method is useful for:

1. **Object Detection**: Isolating objects from the background for analysis.
2. **Image Segmentation**: Dividing an image into distinct regions for further processing.
3. **Feature Extraction**: Simplifying an image to highlight specific features, making them easier to analyze.
4. **Noise Reduction**: Removing minor variations and focusing on significant structures in an image.

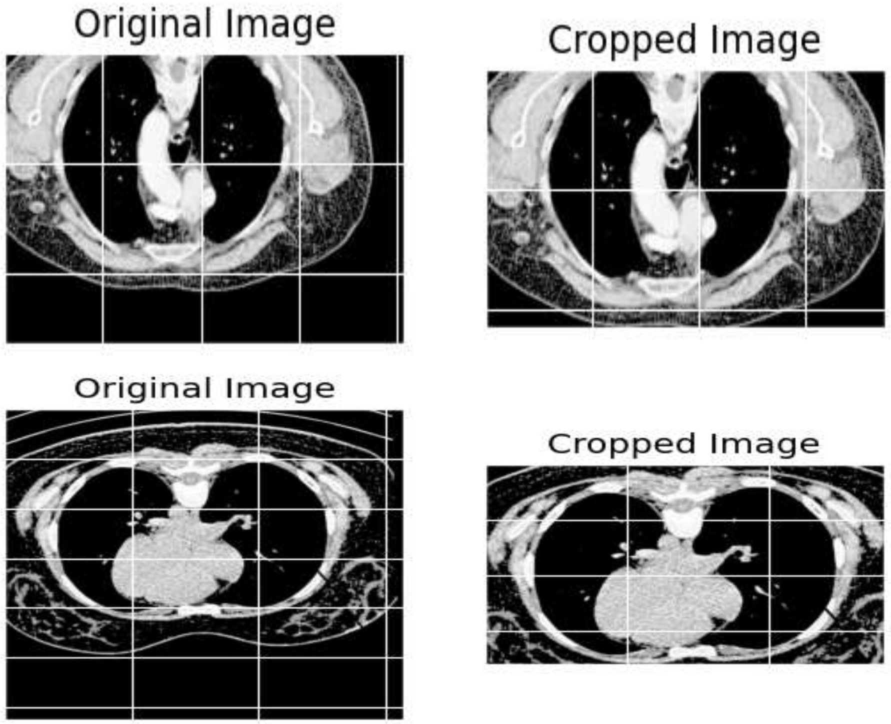


Fig. 3.3.1: Original images and cropped images

3.3 Model Architecture Selection: Our model uses VGG-19. Deep layers and excellent image classification performance make VGG-19 a powerful CNN architecture. The architecture has fully linked layers after convolutional and pooling layers. The convolutional neural network (CNN) architecture will be built using the VGG-19 model, which includes 16 layers for input and 3 layers for output. This VGG-19 model will then be trained with a specified training set, leading to the creation of a training model that will be used for future lung cancer diagnoses.

3.4 Model Training: This level involves four steps. In this article, we will briefly explore the training method employed by the CNN using the VGG-19 based MMT-Vin model.

Input: Our model accepts images sized at 224×224 pixels to maintain a consistent input size.

Convolutional Layers: As its name implies, VGG-19-based MMT-Vin has 19 layers, including convolutional, max-pooling, and fully linked layers. Convolutional layers are essential for extracting visual characteristics. The network consists of blocks with max-pooling layers and numerous convolutional layers. Convolutional layers employ 3x3 filters with a stride of 1 and no padding in order to maintain the input spatial dimensions.

As we progress further into the network, each convolutional block has more layers, allowing the model to learn more complicated characteristics. VGG-19 features five ConvBlocks and sixteen convolutional layers.

Max-Pooling layers: VGG-19 uses max-pooling layers with a window size of 2x2 and a stride of 2 after each convolutional layer. These max-pooling layers reduce computational complexity and capture translation-invariant information by downsampling feature maps' spatial dimensions.

Fully-connected layers: Each layer has highly linked neurons that are coupled to all neurons in the previous layer. As classification progresses, the number of neurons in completely linked layers decreases toward the output layer, corresponding to output classes or categories.

3.5 Model Evaluation: The image dataset will be used to evaluate performance throughout the process. The testing dataset will be fed to the trained CNN model to calculate accuracy, loss, precision, and recall.

3.6 Deployment: The model can classify lung cancer photos once it performs well. Histopathology images are used to detect lung cancer during deployment. The CNN, a deep learning model, receives the input image's unique properties. This stage classifies lung cancer images using the CNN model.

4. Results and Discussion: This study gathered both malignant and benign lung cancer images for the experiment. To ensure effective learning for the CNN model, the dataset needs to be diverse and well-labeled. Lung cancer histology images were sourced from Kaggle for this research. The collection comprises more than 4,000 annotated lung cancer histology images. To facilitate the training and testing processes, the dataset will be split in a 70 to 30 ratio, with 70 percent allocated for the training set, 15 % for testing and 15% for validation purpose. The testing dataset will be used to calculate CNN model accuracy, loss, precision, and recall. This process evaluates CNN model performance.

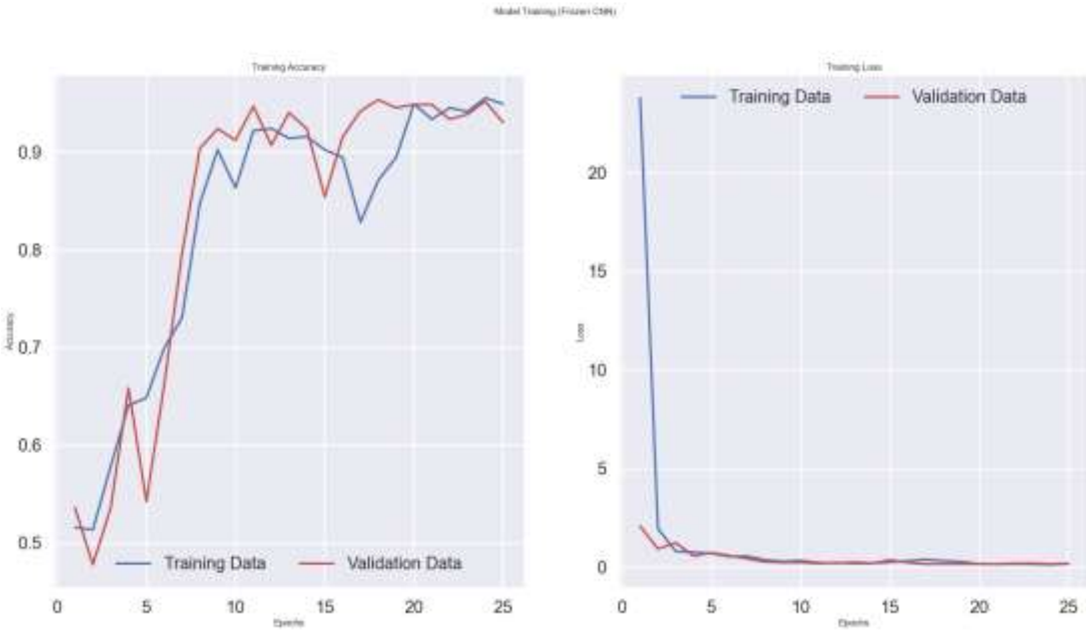


Fig. 4: Model Training Graphs

This section provides a comparative evaluation of the lung cancer prediction model's performance across two experimental sets with different epoch values. The analysis emphasizes the model's convergence behaviour in relation to the number of training epochs. Convergence refers to the stage where the training process stabilizes, leading to a plateau in the model's performance, with subsequent training iterations yielding diminishing returns. By comparing the convergence patterns observed with 20 and 25 epochs, insights can be gained regarding the optimal training duration for achieving satisfactory performance. Performance scores for 20 epochs are detailed in Table 4.1, while those for 25 epochs are presented in Table 4.2.

Table 4.1: Performance results of the Proposed CNN with VGG-19 (epoch 20)

Accuracy	**Loss**	**Precision**	**Recall**
0.93	0.17	0.93	0.93

Table 4.2: Performance results of the Proposed CNN with VGG-19 (epoch 25)

Accuracy	**Loss**	**Precision**	**Recall**
0.98	0.12	0.97	0.97

Thus, the results summarize the outcomes of the experiments carried out over two different time periods (20 and 25 epochs) and highlights their importance in improving the accuracy of the lung cancer prediction model, surpassing previous studies.

5. Conclusion: Deep learning offers several advantages over various machine learning algorithms, the most notable being its ability to perform feature engineering autonomously. This capability allows it to analyze data to identify similar characteristics and integrate those features for faster learning. In recent years, deep learning methods like Convolutional Neural Networks (CNNs) have revolutionized medical image processing. CNNs are particularly well-suited for image-based medical diagnostics as they can analyze complex visual patterns and extract valuable information from images. Once the CNN algorithm has successfully completed its training and testing phases, it will classify the input lung image as either normal or abnormal. For this reason, a Deep Convolutional Neural Network (CNN) utilizing the VGG-19 model was employed in this methodology for predicting lung cancer using histopathological images. VGG-19 is not a separate model from CNNs but rather a specific architecture within the CNN framework. When evaluating CNN architectures, it's crucial to consider their performance. The results of this experiment indicate that the CNN with VGG-19 outperforms other CNN results. Future research should focus on incorporating additional lung cancer image datasets and identifying a more precise model for lung cancer prediction based on these images.

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