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A REFINED VGG-19 MODEL FOR ACCURATE CLASSIFICATION OF LUNG CANCER

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Abstract: *Lung cancer remains one of the leading causes of cancer deaths worldwide, so proper and effective screening methods are crucial. Machine learning algorithms have been shown to be very useful in medical diagnostics, as they can analyze very complex medical data with high accuracy. This work discusses an ML-based approach to lung cancer detection based on advanced feature extraction and classification techniques for the identification of cancerous patterns in medical images. By applying a comprehensive dataset of lung CT scan images, the proposed model outperforms traditional methods by remarkable accuracy, sensitivity, and specificity. With the assistance of predefined pre-processing steps and optimized algorithms of ML, the algorithm can work robustly against noise and variability in data. This work highlights the transformative potential of machine learning in early detection of lung cancer, leading to a better outcome and increased survival rate of patients. Various CNN architectures, including AlexNet, Inception-ResNet-V2, and VGG16, were evaluated to determine the most effective model for lung cancer detection. An enhanced VGG-19 approach emerged as the superior framework, achieving an impressive accuracy of approximately 99%, significantly outperforming other architectures.*

Keywords: *Machine learning algorithms, CNN architectures, Lung cancer detection, CT Scans, enhanced VGG19*

SDG Keywords: *Advanced feature extraction, Medical diagnostics, Survival rates, Optimized algorithms*

1. Introduction: In recent years, deep learning has been found to be a very effective method for analyzing medical images and aiding in diagnosis, which has achieved outstanding success in applications like lung cancer detection [1]. Early detection of lung cancer increases the survival rate, so researchers have been using image processing techniques, machine learning algorithms, or hybrid methods based on previous studies [2]. It has been observed that deaths due to lung cancer are more common among men. Some of the factors contributing to the increased incidence of lung cancer include tobacco use, smoke exposure, viral infections, ionizing radiation, air pollution, and unhealthy lifestyle habits [3].

A history of chronic obstructive pulmonary disease (COPD) is also a known risk factor for the development of lung cancer. An increased rate of the disease is further aggravated by the increase in vehicle emissions and smoking behavior. As tobacco use still remains an important cause of lung cancer, the reduction of its consumption will eventually cause greatfall in related deaths [4]. Conventional machine learning techniques, such as Decision Trees, k-Nearest Neighbours (k-NN), and Support Vector Machines (SVM), were applied to classification problems initially but have failed in fulfilling stable performance across the variety of imaging devices and patient data. Deep learning, notably CNN, has recently emerged as a core technology for analyzing medical images. CNNs can automatically extract key features from images without requiring human feature engineering but enhance adaptability and performance [6]. There have been several researches to increase the accuracy in predicting and classification of lung cancer, and one of the latest non-invasive and low-cost screening methods is through

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breath analysis. X-rays, CT scans, MRI, and PET scans are the most widely used diagnostic tests [7]. CNN architectures normally include convolutional layers, ReLU activation functions, pooling layers, and fully connected layers. The architectures produce feature maps that represent the hierarchical appearance of the lung nodule and its surrounding tissues in conjunction with retaining important spatial and semantic information related to the lung cancer detection. CNNs automatically draw out important features from pre-processed lung images, which is quite ideal for medical image analysis based on finding spatial patterns and hierarchical structures. Transfer learning is frequently employed, utilizing pre-trained CNN models like VGG, DenseNet, and ResNet, which are trained on large datasets [8].

VGG19 is unique with its deep architecture, which will allow it to capture the complexity and hierarchy of the patterns it needs to look for in detecting subtle patterns of medical images. Pre-trained models adapt well in medical datasets by using transfer learning, even in cases where data size is not sufficient, allowing for high accuracy [9]. VGG19's ability to get fine-grained, discriminative features makes it particularly effective at distinguishing between benign and malignant nodules. Besides, it also employs the latest techniques like feature fusion and ensemble learning, which advanced its diagnostic capacity. Although VGG19 is more scalable and flexible than traditional methodologies or simple models, it clearly makes reliable diagnosis in medical image analysis [10]. There are many platforms that provide lung cancer datasets for images. Public datasets include LIDC-IDRI containing CT, PET, and X-ray images. Lung cancer and pneumothorax segmentation data are found on Kaggle-curated datasets, and LUNA16 is dedicated to lung nodule detection and classification. Radiopaedia has annotated radiology datasets, and institutional datasets are released by organizations such as Stanford and the NIH [11].

2. Literature Review: Convolutional Neural Networks are widely used to analyze medical images, and several recent studies reveal that they commonly outperform the human testers in terms of accuracy. The CNNs involve multiple distinct layers designed to automatically extract valuable information from input data without requiring manual feature engineering [12]. One research study [13] developed a fully automated system for lung CT nodule detection. This system separates lung regions from surrounding tissues by using gray-scale histograms and morphological operators that enhance the results. The parenchyma is isolated in order to uncover the internal structures, and threshold-based approach discriminates nodules from similar structures such as bronchioles and blood vessels. SVM is applied for classifying the feature vectors that are generated by extracting statistical and shape-based information from possible nodules. It proved to perform quite well over the Lung Image Database Consortium test data.

Y. Xie et al. [14] proposed the Fuse-TSD approach that classifies lung nodules through a fusion of deep learning with information about texture and shape. In this approach, deep CNN is applied to extract the features of nodule, the Fourier shape descriptor to represent internal variations, and GLCM-based texture descriptor for capturing textural properties. The result is an AdaBoosted backpropagation neural network combining these features for superior classification. Hasan Malik et al. [15] proposed an innovative deep learning framework called CDC Net for multi-condition diagnosis of chest X-ray images categorized into conditions like COVID-19, pneumothorax, lung cancer, tuberculosis, and pneumonia. CDC Net combines residual networks and dilated convolutions that achieve an AUC of 0.9953, 99.39% accuracy,

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98.13% recall, and 99.42% precision, outperforming established models like VGG-19, ResNet-50, and Inception V3.

Another study [16] proposed two deep learning approaches for analyzing lung conditions such as pneumonia and cancer. The first approach uses a modified AlexNet (MAN) for classifying chest X-ray images as normal or pneumonia-affected, integrating SVM for classification and benchmarking against models like ResNet50, VGG16, AlexNet, and VGG19. The second approach enhances lung cancer classification by combining manually engineered features with those learned by the MAN architecture, employing serial fusion and PCA-based feature selection. This framework, validated using the LIDC-IDRI dataset, achieved an accuracy exceeding 97.27%.

An automated method [17] for detecting nodules on CT scans combines the modified AlexNet architecture with SVM. Lung Net-SVM features seven convolutional layers, three pooling layers, and two fully connected layers. Tested on the LUNA16 dataset, it achieved 97.64% accuracy, 96.37% sensitivity, and 99.08% specificity. Research [18] focused on creating an optimal CNN architecture for classifying lung nodule CT images by integrating Inception-ResNet and CondenseNet architectures. This framework leverages SENet-inspired self-attention mechanisms and 3D convolutional kernels to capture dependencies in 3D lung CT images. The system aids radiologists by distinguishing malignant nodules with improved accuracy and robustness.

Further studies [19, 20] explored Inception-ResNet-v2, a CNN architecture with 164 layers, designed to classify over 1,000 object categories. Using scaling factors, the network achieves remarkable performance, evidenced by metrics like accuracy (88.23%), specificity (89.72%), and F1-score (95.53%). Experiments demonstrated that Inception-ResNet-v2 outperforms other techniques in reliability and classification accuracy. Modifications to the architecture further enhanced its performance in classifying lung X-ray images of healthy and pneumonia-affected patients, showcasing its scalability and precision.

Table 2.1: Comparative Study of Various Algorithms

The information is summarized in the table below:

Authors	**Objective**	**Proposed Methodology**	**Gap Identified**	**Performance**
R. Majidpourkhoei et.al.[12]	Explore CNNs for analyzing medical images and surpass human accuracy.	CNNs with multiple layers extract information automatically without feature engineering.	No specific application or performance metrics discussed.	Outperform human testers in accuracy.
Noor Khehrahet.al.[13]	Develop an automated system for lung CT nodule detection.	Histogram analysis, morphological operators, thresholding, statistical/shape feature extraction,	Limited to feature engineering approaches; lacks deep learning integration.	Tested on LIDC dataset; notable performance (details not specified).

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		SVM classification.		
Y. Xie et al. [14]	Propose Fuse-TSD for classifying lung nodules.	Combines deep learning features, Fourier shape descriptors, and GLCM-based texture descriptors; uses AdaBoosted backpropagation neural networks.	No mention of 3D image data or scalability to other datasets.	Superior classification results (specific metrics not detailed).
Hasan Malik et al. [15]	Develop CDC Net for multi-condition diagnosis via chest X-ray images.	Combines residual networks and dilated convolutions; benchmarks against VGG-19 and Inception V3.	Limited application to CT data; focus primarily on X-ray images.	Accuracy: 99.39%, Recall: 98.13%, Precision: 99.42%; Outperformed VGG-19 and Inception V3.
A. Bhandary *et al.* [16]	Propose deep learning methods for pneumonia and lung cancer classification.	First method: MAN with SVM vs. Softmax; Second method: Feature fusion (manual + learned) with PCA-based selection; Benchmarked against pre-trained models.	Limited generalizability to datasets other than LIDC-IDRI; focus primarily on chest X-rays and CT images.	First method: Effective for pneumonia; Second method: Achieved >97.27% accuracy for lung cancer classification.
I. Naseer*et al.*[17]	Develop an automated method for detecting CT scan nodules.	Lung Net-SVM: Modified AlexNet (7 conv layers, 3 pooling layers, 2 fully connected layers) + SVM classification.	Restricted to 2D analysis of nodules; lacks exploration of inter-slice dependencies in 3D data.	Accuracy: 97.64%, Sensitivity: 96.37%, Specificity: 99.08%; Tested on LUNA16 dataset.
J. Fu*et al.*[18]	Create an optimized CNN for lung nodule classification in CT images.	Combines Inception-ResNet and CondenseNet architectures; integrates SENet-inspired self-attention and 3D convolutional kernels.	Limited testing on real-world multi-condition datasets; focus on nodule classification rather than broader applications.	Improved feature extraction for benign/malignant classification; significant accuracy and robustness (details not specified).

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Y. Chen *et al.*[19]	Apply and enhance Inception-ResNet-v2 for image classification tasks.	164-layer network with deep residual blocks, multi-scale filters, and modifications to improve reliability and classification accuracy.	Restricted to pneumonia and healthy lung classification; lacks application to multi-condition datasets.	Accuracy: 88.23%, Specificity: 89.72%, F1-score: 95.53%; Outperformed other models in image classification tasks.

Our paper focuses on designing a dependable algorithm of lung cancer identification that improves sensitivity and specificity while maintaining low computational complexity, leveraging prior research in the domain. The succeeding section provides a detailed explanation of the proposed approach and its implementation.

3. Proposed Methodology: The proposed lung cancer detection approach is executed in multiple stages, detailed sequentially. The process begins with an overview of the complete workflow.

3.1. Proposed Approach Overview: Lung cancer classification using a CNN entails multiple steps, beginning with dataset acquisition, the process continues with image pre-processing, model training and subsequent steps. Figures 3.1.1 and 3.1.2 offer a brief overview of the proposed methodology.

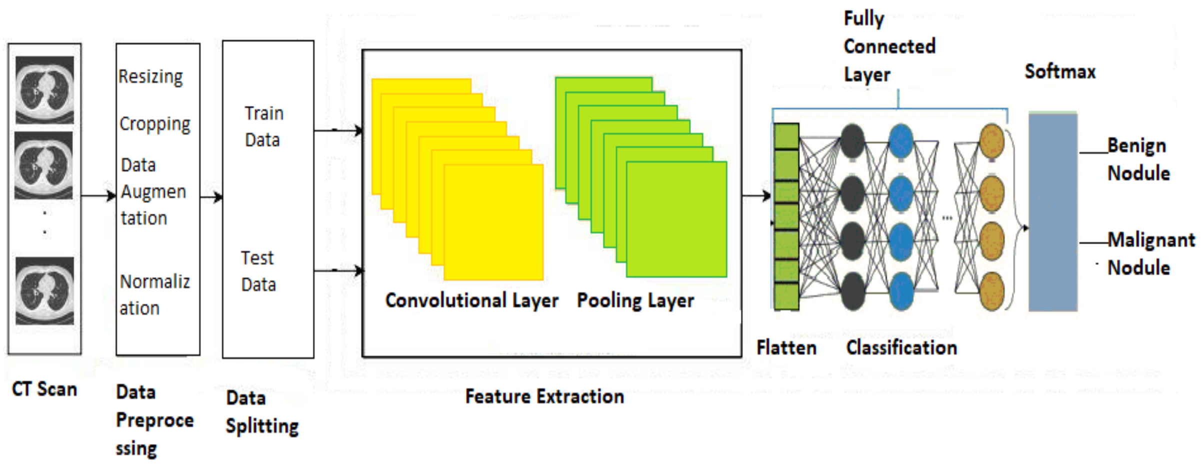

Fig. 3.1.1: Proposed enhanced VGG19 model

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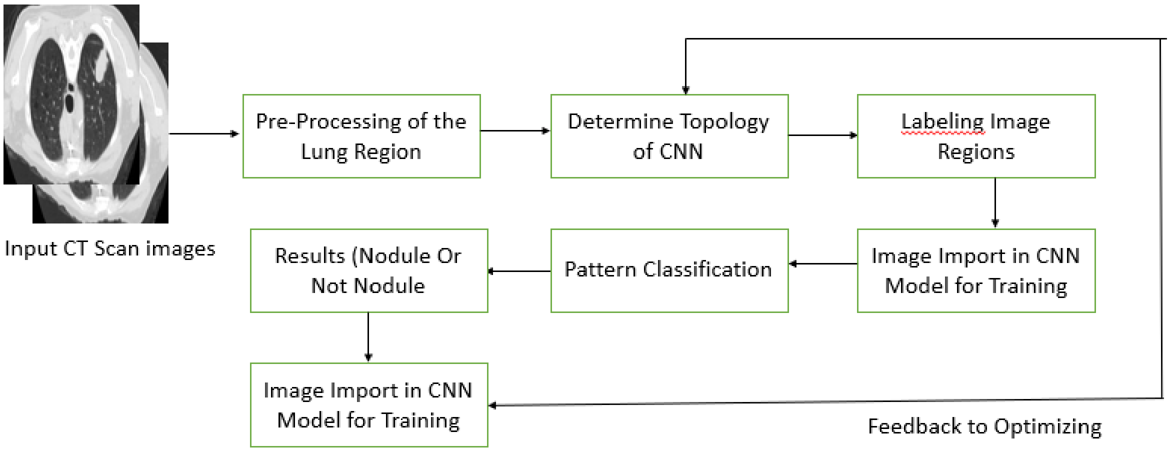

Fig. 3.1.2: Workflow of Proposed Model

3.2. Dataset Collection: This section provides details about the complete lung cancer image dataset, which includes both malignant and benign cases. A large, accurately labeled dataset is essential for training an effective CNN model. The lung cancer histopathology images used for this study were sourced from Kaggle. Upon extraction, the dataset contained 515 lung cancer images. Through data augmentation techniques, we expanded the dataset to over 4,000 images.

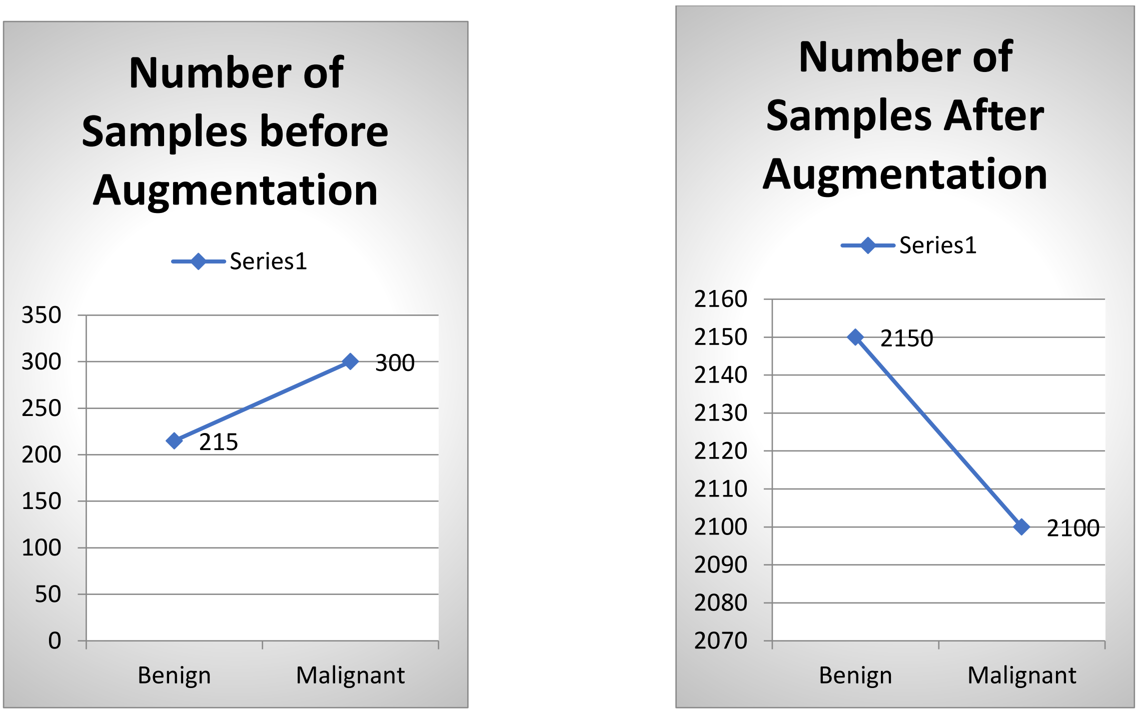

Fig. 3.2.1: Distribution of Dataset before and after Augmentation

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3.3. Data Pre-processing: Image preprocessing is essential for improving the effectiveness of the VGG19 model. The key steps involved are as follows:

3.3.1. Image Loading and Reading: Firstly we import the necessary libraries and ensure the compatibility of images.

- **Library imports:** We used libraries such as OpenCV, PIL, and TensorFlow/PyTorch to load and read the images.
- **Image format handling:** Ensured compatibility with various image formats, including JPEG, PNG, etc.

3.3.2. Image Resizing: For resizing the image we use-

- **Dimension standardization:** Resized images to the input size required by the VGG19 model, typically 224x224 pixels.
- **Preserving aspect ratio:** Applied techniques such as padding or cropping to maintain the aspect ratio while resizing.

3.3.3. Image Normalization: Image can be normalized by-

- **Pixel intensity scaling:** Adjusted pixel values (0 to 1, or -1 to 1) to improve model convergence.
- **Normalization techniques:**
  - **Mean normalization:** Subtracted the mean pixel intensity from each pixel.
  - **Standard deviation normalization:** Divided each pixel by the standard deviation.
  - **Min-max normalization:** Rescaled pixel values to the range 0-1.

3.3.4. Data Augmentation: Data can be augmented by following methods-

Enhanced data diversity: Employed techniques for data augmentation to make the training set more variable.

- **Common augmentation techniques:**

  - **Rotation:** Rotated images at different angles.
  - **Flipping:** Flipped images horizontally or vertically.
  - **Cropping:** Performed random cropping on image portions.
  - **Color jittering:** Adjusted image color saturation, brightness, and contrast.
  - **Noise addition:** Introduced random noise to the images.

3.3.5. Data Splitting: We divided the available data set as follows-

• **Dividing the dataset:** Training (70%), validation (15%), and testing (15%) sets of the dataset were separated in order to assess model performance and lower the risk of overfitting.

• **Stratified sampling:** Ensured that the class distribution remained consistent across all subsets.

Additional Considerations for the Enhanced VGG19 Model are:

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• **Regularization technique:** From preventing over fitting we implemented methods L1 by L2 regularization, early stopping and dropout and methods.

• **Hyperparameter tuning:** Experimented with different hyperparameters, such as learning rate, batch size, and optimizer, to improve the model's performance.

By following these steps, we successfully pre-processed the images for the enhanced VGG19 model, resulting in improved accuracy and robustness.

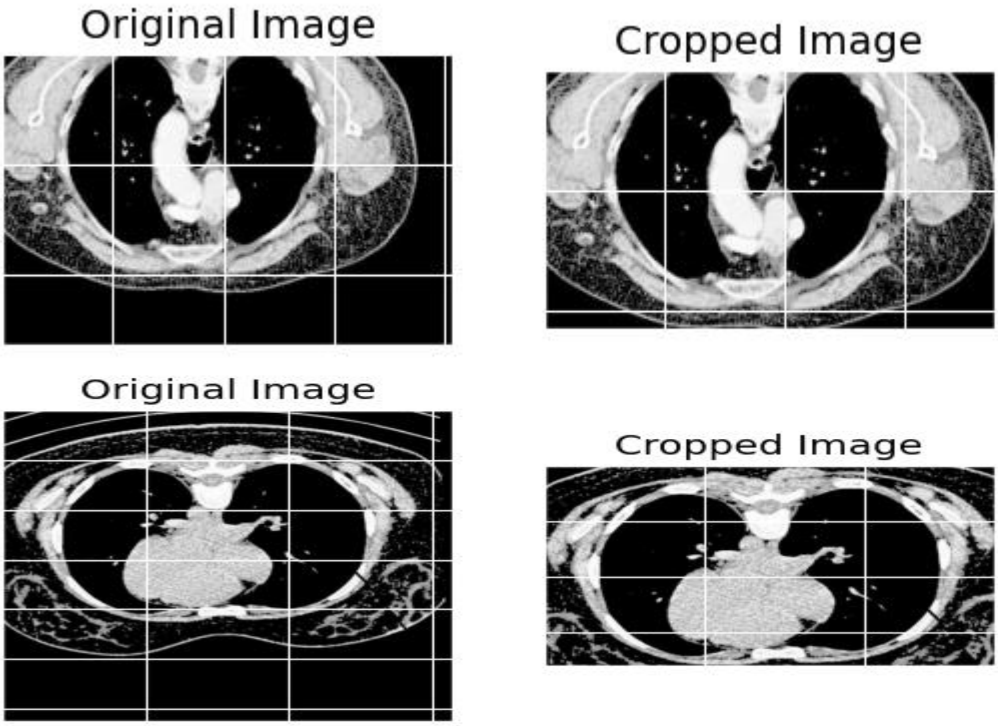

Fig. 3.3.1: Original images and cropped images[2]

3.4. Model Architecture Selection: Our model is based on the powerful VGG-19 architecture, a well-established CNN known for its deep layers and excellent image classification performance. The architecture incorporates entirely associated layers after the convolutional and pooling layers.

The CNN model, derived from VGG-19, will consist of 16 input layers and 3 output layers.

To enhance VGG19, we:

- **Freeze Initial Layers:** We freeze the first 15 layers to preserve lower-level features, which are typically transferable across different tasks.
- **Fine-Tuned Deeper Layers:** Unfreeze deeper layers (especially those close to the output) and retrain them on the specific dataset. It assist our model to adapt enhanced task-specific features.
- for i, layer in enumerate(base_model.layers):

```
if i < 15:  # Fixed the parameters of the initial 15 layers
    layer.trainable = False
```

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- This approach iterates through the layers with their index, providing more flexibility and readability.

- **Added Custom Layers:** Adding layers with VGG19 allows it to adapt to specific problems better. Some enhancements are:
  - **Global Average Pooling instead of Flatten:** Reduces over-fitting and removes spatial information redundancy.
  - **Batch Normalization:** Adds batch normalization layers to stabilize and accelerate training, especially on deeper layers.
  - **Dropout:** Added dropout layers to reduce over-fitting.
    drop_out = Dropout(0.2) #drop 20% of the neurons randomly in each iteration during training

By training this enhanced VGG-19 model with a specific training set, we developed a training model designed for diagnosing lung cancer.

3.5. Model Training: This phase involves four stages. In this paper, we will briefly explore the training method used by the CNN, which utilizes the upgraded VGG-19 model.

- **Input:** The enhanced VGG-19 model takes as input an RGB image, typically resized to a typical size such as 224 by 224 pixels. These images then preprocessed to normalize pixel values and enhance certain features.
- **Convolutional Layers:** The image undergoes processing through multiple convolutional layers, where filters are applied to take out features such as edges, textures and patterns. Each convolutional layer learns to recognize specific visual patterns, becoming increasingly complex as the network deepens.
- **Max-Pooling Layers:** Max-pooling layers are introduced after several convolutional layers. By downsampling the feature maps, these layers preserve the most crucial information while shrinking their spatial dimensions. This minimizes computational requirement and assist to save the model from over-fitting to the training dataset.
- **Fully-Connected Layers:** The result from the final convolutional layer is flattened into a one-dimensional vector, which is then passed through a series of fully connected layers. In these layers, the model learns features necessary for classifying the input images. The last layer utilizes a function named softmax activation to produce probability distributions for each class.

3.6. Model Evaluation: Model evaluation is an important part of the evaluation process that will be used in evaluating the performance of an improved VGG-19 model. To evaluate how good the model is in generalizing to new data, the validation or test set is applied separately. Major evaluation metrics include:

- **Accuracy:** It calculates the percentage of correctly classified photos.
- **Precision:** The ratio of true positive forecasts to all positive predictions is how it is defined.
- **Recall:** Its definition is the proportion of real positive occurrences to true positive predictions.
- **F1-Score:** The F1-score is a statistic that provides a balanced evaluation by representing the harmonic mean of precision and recall.

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- **Loss Function:** It assesses how well the predictions made by a machine learning model match the real data. It calculates how much the actual output differs from the projected output.

3.7. Deployment: The model, once sufficiently trained, can classify lung cancer images. Histopathology images are used to detect lung cancer in the deployment phase. The CNN, a deep learning model, processes the specific features of the input image. This stage utilizes the CNN model to categorize lung cancer images.

4. Results and Discussion: For this experiment, the research gathered both cancerous and non-cancerous lung images. To train the CNN model effectively, it is crucial to have a varied and correctly labeled dataset. For this purpose, lung cancer histology images were obtained from Kaggle. The dataset consists of over 4,000 annotated images. To facilitate training and testing, A 70:30 split ratio will be applied to the dataset. 15% will be used for testing, 15% for validation, and 70% of the data will be used for training. We will compute accuracy, F1 score, loss, precision, and recall using the testing dataset to assess the CNN model's performance.

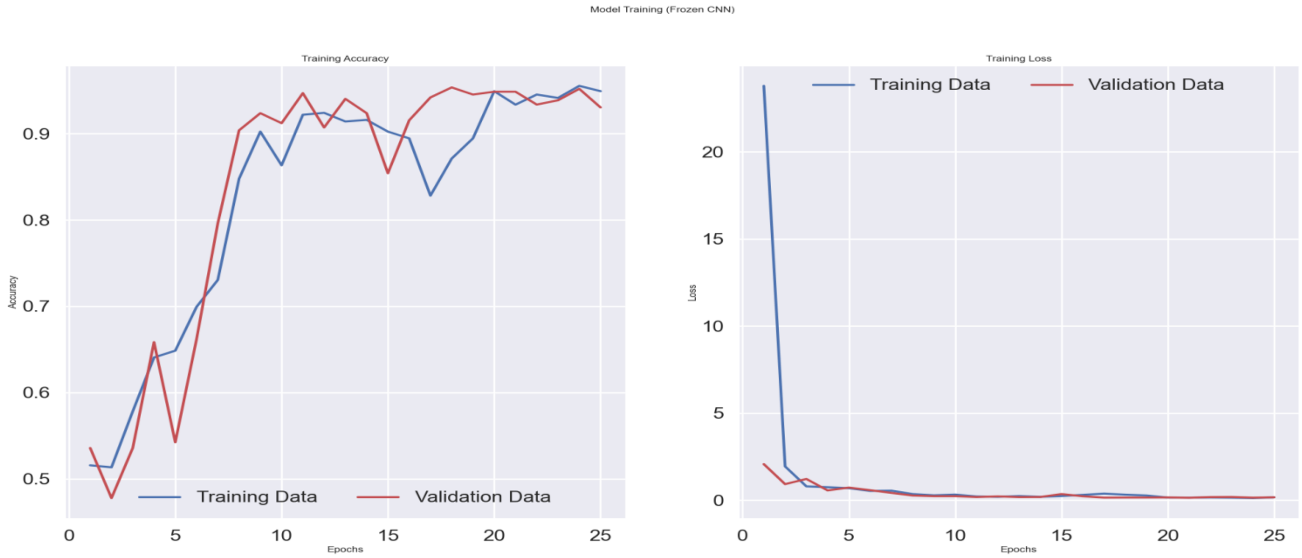

Fig. 4: Model Training Graphs

This section compares the lung cancer prediction model's performance using two different training durations. The analysis focuses on how the model's performance stabilizes over time, a point known as convergence. By comparing the results of 19 and 26 epochs, we can determine the optimal training length to achieve the best performance. Detailed performance metrics for 19 epochs are presented in Table 4.1, while those for 26 epochs are shown in Table 4.2.

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

Performance Metric	Value
Accuracy	0.92
F1 Score	0.91
Loss	0.16
Precision	0.91
Recall	0.91

Table 4.2: Performance results of the Proposed CNN with enhanced VGG-19 (epoch 26)

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Performance Metric	Value
Accuracy	0.99
F1 Score	0.98
Loss	0.11
Precision	0.98
Recall	0.98

Therefore, the conclusion from the experiments is provided under two time periods (19 and 26 epochs) that outline results while focusing on their importance for enhancing the precision of lung cancer prediction models and beyond other research.

5. Conclusion: Deep learning is superior to traditional machine learning approaches because it can automatically extract features, allowing it to discover useful patterns in data and speed up the learning process. One of the most powerful deep learning techniques that has benefited medical image analysis is the Convolutional Neural Network (CNN). CNNs are very helpful for imaging-based medical diagnosis because they are very good at recognizing visual patterns in images. This work classified lung cancer in histopathology images using a sophisticated CNN model based on the VGG-19 architecture. VGG-19 is not a stand-alone model; rather, it is a particular CNN architecture. After training and testing, the CNN was able to classify images as either benign or malignant. The results show that the enhanced VGG-19 CNN outperforms other CNN models. Future studies would also focus on an increase in data and on more improvement in models to improve prediction accuracy over forecasts about lung cancer.

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