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Transfer Learning Approach on Lung Cancer Detection System

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Abstract— ***The prevalence of lung cancer has increased significantly, attributed to lifestyle modifications, alcohol consumption, hereditary factors, and exposure to environmentally-dispersed hazardous gases. The disease is affected by genetic abnormalities and exposures from industries like construction, manufacturing, and mining. The identified research challenges highlight limitations in current approaches, emphasizing the importance of developing an early detection framework, reducing false-positive rates, and ensuring accurate classification. However, there are concerns regarding convolutional neural networks (CNNs) in the proposed model, including increased processing latency, particularly with deep processing needed for high-resolution data. Efforts to mitigate this issue involve minimizing GPU usage when handling high-definition images. The proposed approach integrates transfer learning, employing the ensemble concept with the VGG16 network known as TLA-VGGN. The system's performance is evaluated based on accuracy and error rate, achieving 99.02% accuracy with a validation loss of 0.920. The training utilized a dataset of 2901 images across four classes, successfully identifying 568 images representing different cancer types.***

Keywords— ***Lung cancer, Transfer learning, Machine learning, Deep learning, CNN, Ensemble architecture.***

I. INTRODUCTION

Lung cancer is becoming increasingly common due to various lifestyle changes, genetic predisposition, alcohol consumption, exposure to hazardous environments, and exposure to air pollution. The disease has two main types: small cell lung cancer (SCLC) and non-small cell lung cancer. Non-small cell lung cancer has subtypes such as adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. SCLC is particularly severe, with a low survival rate. In some cases, a combination of SCLC and non-small cell lung cancers may occur. Early-stage detection often involves ultrasound imaging (USD). Advanced lung infection diagnosis requires computed tomography (CT) imaging and Magnetic Resonance Imaging (MRI). Histopathology imaging techniques are employed in lung cancer detection systems, augmenting clinical patient history for accurate examination. The growth of machine learning technology, computer vision, and image processing techniques is prevalent in lung cancer detection systems. In the existing state-of-the-art approach [3], a support vector machine with a relief algorithm achieves an accuracy of 83.91%. In some instances, the initial screening process begins with X-ray projections. Segmentation and localization of cancer regions from lung X-ray images are crucial. Volumetric analysis using a convolutional neural network (CNN) is present. Cancer infections in CT images were identified based on variations in intensity, with image pixel intensity serving to distinguish between normal and infected areas across all imaging techniques [4]. Various datasets from public domains were utilized for modelling lung cancer detection. In the existing system, a deep learning model and knowledge-based collaborative system achieved 91.6% accuracy using the LIDC-IDRI dataset [5].

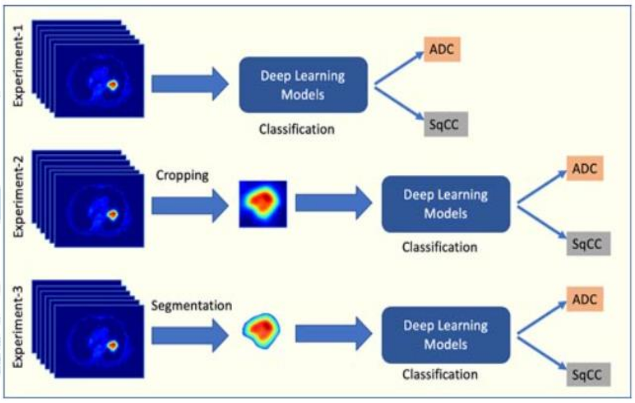

Figure 1. Metastates activity of cancer cells *M. Bicakci et al. (2020)*

Figure 1. Illustrates the metastatic activity identified by a deep-learning model. Tracking lung cancer spread to other organs using X-ray images poses challenges due to low resolution and increased noise. It is imperative to monitor lung cancer metastasis to other organs and identify the spread of infected lung cells. Early detection of lung cancer is essential for mitigating associated survival challenges. The proposed system recognizes early detection as a critical aspect and assesses a framework to accomplish it.

- Reducing The false negative rate that leads to deviations in the treatment procedures is reduced by increasing the accuracy through the recurrent learning process.
- Early detection of cancer can reduce the need for aggressive treatment procedures, whereas detecting cancer at an advanced stage can cause intense pain and

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severely impact the survival rate of patients. In addressing this concern, the proposed approach emphasizes analyzing survival rates through meta-analysis, attaining precise cancer detection, and minimizing false positive outcomes.

II. RELATED WORK

D. Xiang et al. (2023) Lung cancer segmentation through (PET) positron emission tomography, and CT images are discussed here. Modality-specific segmentation network is developed here to encode the common feature present in the test images compared with the training images of normal patients as well as abnormal patients. 126 PET-CT images are utilized for learning purposes and to fix the model evaluation. The presented system is compared with various state of art approaches but still, the challenging part of the existing work is the noise present in the input data, and unbalanced features in each image [7].

P. Zhou et al. (2023) The author presented a system on multiple attention coordinate networks for lung cancer detection using a semantic bidirectional algorithm. The high dimensional semantic features are utilized to classify non-small cell lung carcinoma and small cell lung carcinoma. The effectiveness and stability of the detection model are evaluated using the Coco attention module. The major challenge in utilizing MRI images is the complex data processing and latency is more [8]. Mohamed et al. (2023) Ebola optimization algorithms that provide deep adaptation support to lung cancer detection framework implemented using a deep learning algorithm. Since various pitfalls still exist in deep learning models, such as large graphical processing unit (GPU) accessibility, reduction in accuracy in case of reduced number of training images, etc, an optimised mechanism is proposed here. The presented system achieved 93.21% accuracy, 90% sensitivity, 79% average specificity etc [9].

- The challenges in the existing state of art approaches are the research problems identified. It is clear and depicted from the implementations so far that the development of an early detection framework, reducing the false positive rate, and accurate classification is important.
- The utilization of CNN in the proposed model consumes more latency in processing. High-resolution data requires deep processing of input images at every level of layers. The massive utilization of graphical processing units (GPU) on high-definition images needs to be reduced.

III. BACKGROUND STUDY

Convolutional Neural Networks (CNNs) represent the most prevalent type of artificial neural network utilized in the realm of deep learning for the recognition of images and videos. These networks inherently adapt to novel inputs, such as images and videos, enabling them to grasp spatial hierarchies of features. CNNs have demonstrated exceptional performance in image recognition endeavours, attaining state-of-the-art outcomes on benchmark datasets like ImageNet. Their efficacy has transcended image-related tasks, extending into diverse domains such as natural language processing and speech recognition. The architecture of a convolutional neural network is represented in Figure 2.

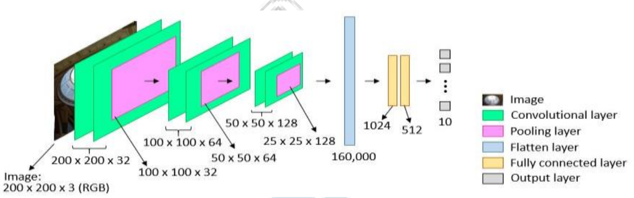

Figure 2. Architecture of a Convolutional Neural Network.

Within the healthcare domain, CNNs find application in the analysis of CT scans, X-rays, and various other medical images. Their role is pivotal in aiding diagnosis and treatment planning. The rising use of CNNs in the medical domain is projected to catalyze significant progress in healthcare by bolstering the accuracy and efficiency of medical image analysis.

IV. SYSTEM DESIGN

In addressing diverse challenges, the proposed model adopts a transfer learning methodology. This strategic choice offers notable advantages, including a significant change in training time and enhanced capability to handle smaller datasets. By capitalizing on the existing knowledge and training patterns obtained from the initial inputs, the model's accuracy experiences a significant enhancement. The essence of the transfer learning strategy lies in the seamless transmission of learned patterns from the primary phase to subsequent blocks. The acquired patterns are not solely utilized in the initial training phase but are also smoothly incorporated into a continuous learning process for new and untested images. To bolster the resilience of the system, Python is selected as the programming language, leveraging its expertise in executing scientific computing algorithms and statistical models.

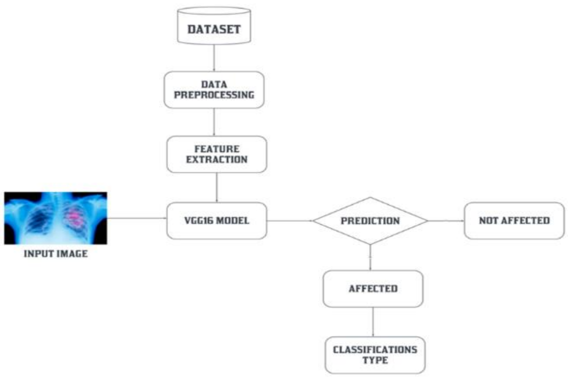

Figure 3. The system architecture of the proposed TLA-VGGN model

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Volume 11 Issue 3 March 2024

Figure 3. Illustrates the system architecture of the proposed lung cancer detection model. Drawing upon the benefits of transfer learning and deep learning algorithms, the system under consideration employs the VGG16 network to facilitate pattern learning with heightened accuracy and a diminished false negative rate. The datasets are obtained from a publicly available website called the LIDC dataset. The images are collected and divided into 80% for training and 20% for testing. Early detection of lung cancer reduces the necessity for aggressive treatment procedures during the advanced stages. Pre-trained image weights are stored in the stacked layers to compare and refine the layers. The VGG network is a straightforward ensemble of layers employing a transfer learning approach.

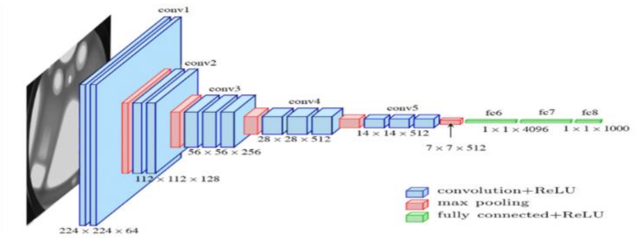

Figure 4. The general structure of the VGG16 network

Figure 4. Shows the general structure of the VGG 16 network in which the input layer contains 224x224x64 dimensions, followed by the convolution layer of 112x112x128, followed by the convolution layer 56x56x256, in which the layers of next convolution layer 28x28x512. The preceding layer contains 14x14x512 and 7x7x512 max-pooling layers. The fully connected layer is structured with dimensions of 1x1x4096 and is subsequently followed by a layer with dimensions of 1x1x1000, serving as the output layer. The outcome of the system architecture VGG16 network provides the accurate extraction of image features.

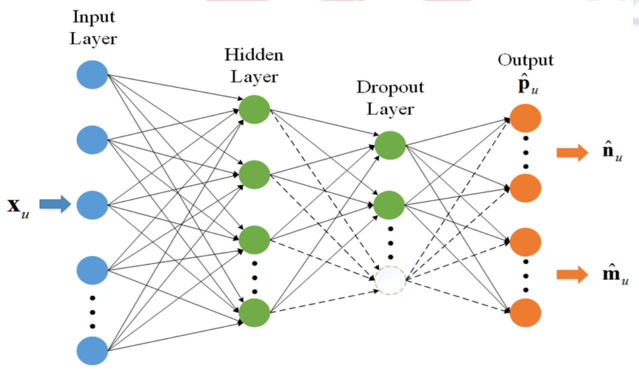

Figure 5. VGG-16 Architecture

Figure 5. Represents the VGG16 architecture that comprises a series of convolutional and fully connected layers. Following the input layer, a dropout layer is not inherently present in the original VGG16 architecture. Dropout layer is a regularization technique widely employed to mitigate overfitting in neural networks. Within the hidden layers, the structure of VGG16 is a sequence of convolutional layers utilizing 3x3 filters. This distinctive arrangement contributes to the feature extraction process within the network.

Table I. VGG 16 Network Configuration

Layer Name	Dimension
Input Layer	224x224x64
Convolution layer 1	224x224x64
Convolution layer 2	112x112x128
Convolution layer 3	56x56x256
Convolution layer 4	28x28x512
Convolution layer 5	14x14x512
Max-Pooling layer	7x7x512
Fully connected layer 1	1x1x4096
Ensemble Fully connected ReLu layer	1x1x1000

Table 1. Shows the VGG16 network model configuration of layers for lung cancer detection. In this dissertation, a pre-trained convolutional neural network (CNN), specifically VGG16, was utilized. The model is obtained from Keras Applications, a repository that offers a range of deep learning models pre-loaded with pre-trained weights. VGG16 is compatible with TensorFlow. Although newer models such as Inception and ResNet have surpassed VGG16's performance and secured victory in the ILSVR (ImageNet) competition in 2014. The default input size for the VGG16 model is 224x224 pixels [64].

V. PROPOSED METHODOLOGY

A. Dataset

The Kaggle dataset of Lung CT-Scan images constitutes a comprehensive collection of lung CT scans intended for the analysis of diverse lung diseases. The dataset comprises images from patients diagnosed with lung cancer, pneumonia, and other respiratory ailments. The dataset features a vast collection of lung CT scans stored in the DICOM (Digital Imaging and Communications in Medicine) standard medical imaging file format. It is a comprehensive repository of chest CT scans for various medical investigations.

B. Data Augmentation

Data augmentation plays a significant role in methodology, mainly in data or image processing. This technique enhances existing data by introducing new information, thereby improving the dataset and the model's performance in the following Figure 6.

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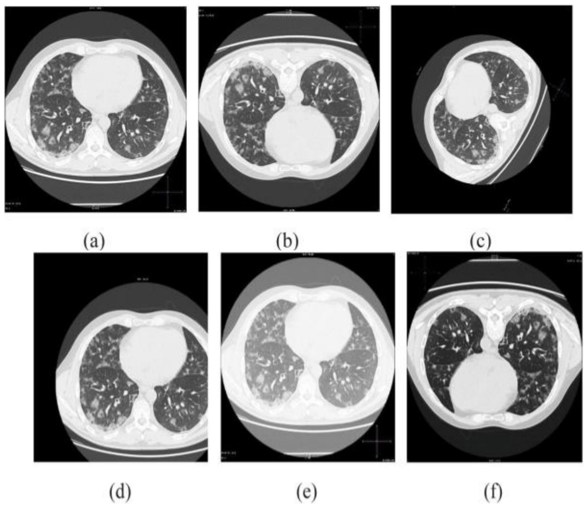


Figure 6. The resulting output after applying the enhancement method.

Table II. Augmentation Technique

Technique	**Setting**
Rotation	45
width_shift	0.2
height_shift	0.2
Shear	0.2
Zoom	0.2
horizontal_flip	True
Fill_mode	Nearest

Table 2. Methodological improvements stemming from the incorporation of augmentative techniques.

C. Experimental Setup

Based on our study, we conducted training and validation experiments on three models: DenseNet201, VGG16, and VGG19, for multi-class classification. Our classification had four classes: normal, adenocarcinoma, squamous cell carcinoma, and large cell carcinoma, with class numbers 0, 1, 2, and 3, respectively. While analyzing the accuracy and loss function plots for DenseNet201, we observed an instability characterized by a significant difference between the training and validation outputs. The training data showed an accuracy of 95.04% with a loss of 0.015, whereas the validation data showed an accuracy of 85.15% with a loss of 0.352. These results imply that the DenseNet201 model could not capture enough information during the training phase to predict new validation data accurately.

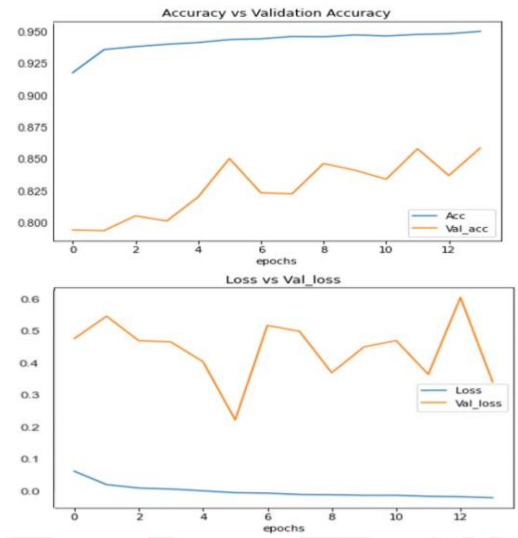


Figure 7. The graph illustrates the accuracy and loss function trends of the pre-trained DenseNet201 model across both the training and validation datasets

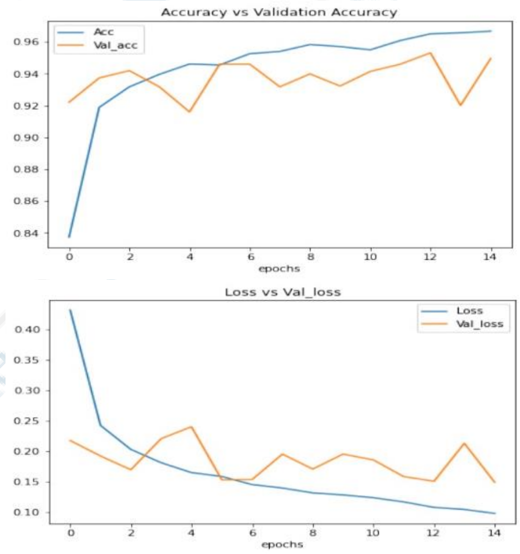
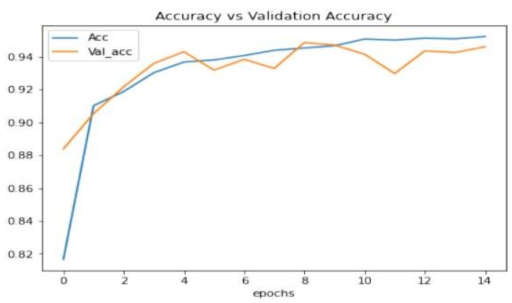


Figure 8. The graph depicts the trends of accuracy and loss functions of the pre-trained VGG16 model across both the training and validation datasets.



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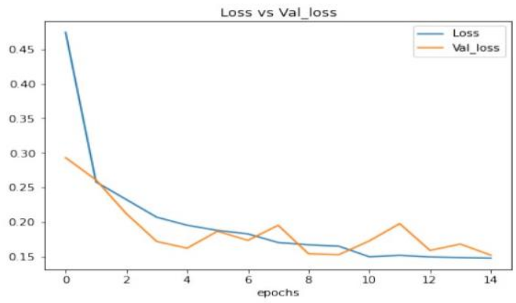

Figure 9. The graph illustrates the accuracy and loss function trends of the pre-trained VGG19 model across both the training and validation datasets

In contrast, the VGG16 model showed robust and efficient performance, achieving a training accuracy of 99.40% with a loss of 0.12. The validation accuracy was 94.25%, with a loss of 0.16. Similarly, the VGG19 model provided excellent results, achieving an accuracy of 94.72% and a loss of 0.152 during training. The corresponding validation metrics were 94.03% accuracy and a loss of 0.156.

Table III. Comparison of the Performance of the Three Pre-Trained Models

Network	Precision	Recall	F1-Score	Accuracy
DenseNet-201	94.07%	88.30%	89.44%	91.97%
VGG16	**95.48%**	**95.41%**	**95.41%**	**95.48%**
VGG19	95.01%	94.95%	94.96%	95.03%

As a result, the model requires more epochs to learn and generalize effectively compared to the VGG16 and VGG19 models.

VI. RESULTS AND DISCUSSIONS

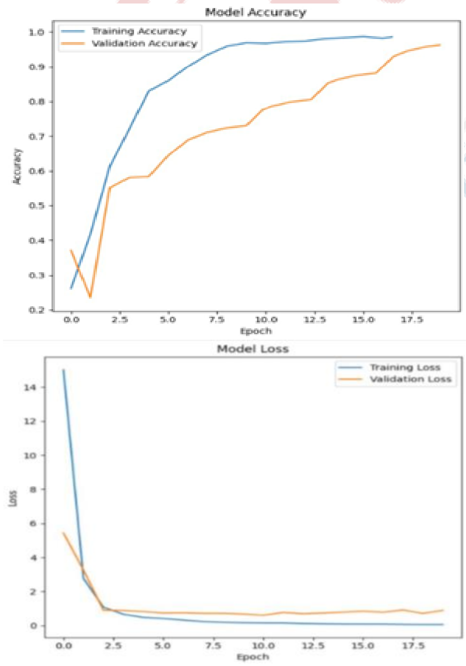

Figure 11. Model Loss and Accuracy

Figure 11. Displays the accuracy and loss of the proposed TLA-VGGN model for lung cancer detection. Real-time test images are retrieved within the web page and processed at the backend. As each epoch progresses, the loss diminishes while the model's accuracy steadily advances towards its zenith. The proposed model achieved an accuracy of 99.02%.

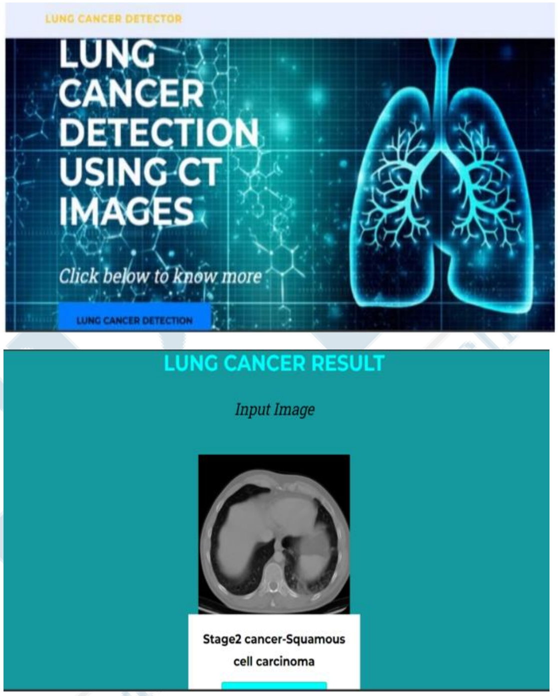

Figure 12. Detection of Cancer

Figure 12. Shows the detection of cancer from the input test image detected as stage 2 cancer-squamous cell carcinoma. After the recurrent iterations in VGG16 architecture, the transfer learning approach produces the classified result as squamous cell carcinoma. The training process of the TLA-VGGN model initiated with epoch 0 to a maximum of 1000 is allowed. During the initial stage itself, the accuracy increased to a certain level due to the TLA. As per the above result, 99.02% accuracy is achieved around 20 epochs. The Validation Loss of 0.9200 and validation Accuracy of 88.90% are obtained.

VII. CONCLUSION

The commonness of lung cancer has expanded fundamentally, ascribed to the way of life adjustments, liquor utilization, genetic variables, and openness to ecologically scattered risky gases. This serious sickness is impacted by hereditary irregularities and a mix of different openings in occupations like development, assembling, and mining businesses. The examination issues distinguished show the difficulties in the present status of the craftsmanship approaches. It is clear from the executions to date that the improvement of an early location structure, the decrease of bogus positive rates, and exact grouping are essential.

The proposed model's utilization of CNN brings about

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Volume 11 Issue 3 March 2024

expanded inertness during handling. Profound handling of information pictures at various layers is fundamental for high-goal information. There is a need to diminish the broad use of graphical handling units (GPUs) while taking care of top-quality pictures. The proposed approach considers the gathering thought of the transfer learning approach (TLA) empowered VGG 16 organization addressed as TLA-VGGN. The framework execution is estimated through the exactness and blunder pace of the cycle. The framework accomplished 99.02% exactness with an approval deficiency of 0.9200 absolutely 2901 pictures have a place with four unique classes decided on preparing. The proposed framework recognized 568 pictures from four classes of cancers.

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