A Lung Cancer Detection using Transfer Learning

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Abstract- Cancer has been the leading cause of cancer deaths for decades. Among the many types of cancer that affect humans, lung cancer is one of the most dangerous. To solve this important problem, our method involves using transfer learning to create a convolutional neural network (CNN) specifically designed to analyze lung CT scans as normal, poor, or poor. In this work, we built a deep neural network based on VGG19, a pre-learned convolutional neural network architecture. A database of 1,500 lung CT scans was used in the study. The classification performance of four different learning algorithms (LeNet, Alex Net, Google Net, and VGG19) over 10 times was comprehensively compared, and VGG19 emerged as the best performer. Our proposed method achieved an accuracy of 92.7% during testing

I. INTRODUCTION

Lung cancer, characterized by the abnormal growth of cells in the lungs, represents a significant threat among various types of cancer. The cells involved in this disease are known as malignant nodules. Utilizing deep learning technology for analyzing CT scan images of the lungs offers unprecedented insights into patient conditions. Lung cancer remains a leading cause of death globally, affecting individuals regardless of gender. Breast cancer is identified as the top cause of cancer-related mortality. Cancer development involves the transformation of normal cells into malignant ones through several stages. This uncontrolled cell proliferation can metastasize to other parts of the body, leading to cancer. When this process occurs in the lungs, it results in lung cancer. Early detection and diagnosis of lung cancer are crucial for effective treatment and survival, as delayed detection can allow the cancer to spread undetected.

Lung cancer is classified into two primary types: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). SCLC, which constitutes about 15% of lung cancers, is known for its rapid growth and tendency to spread aggressively through the airways to other body parts. In contrast, NSCLC, the more common type, is associated with the formation of solid tumors and is generally slower to spread than SCLC. Early detection of NSCLC is essential to prevent its progression and improve patient outcomes. This study concentrates on distinguishing four specific types of lung cancer: adenocarcinoma, large cell carcinoma, small cell carcinoma, and squamous cell carcinoma. Accurate diagnosis often relies on the expertise of medical professionals, which can be a source of concern and complications for patients. Additionally, manual diagnosis may have psychological and financial implications for patients.

Advancements in image processing technology have the potential to enhance the accuracy and efficiency of lung cancer detection. By leveraging techniques such as transfer learning, which involves adapting pre-trained models to new tasks, significant improvements can be achieved even with limited data. Transfer learning allows for the reuse of previously acquired knowledge to address new challenges, akin to how a teacher might use knowledge from identifying foods to classify beverages. This study evaluates and compares the performance of four transfer learning models: LeNet, AlexNet, GoogleNet, and VGG19, in the context of lung cancer classification. The subsequent sections will delve into recent advancements in lung cancer screening, provide a detailed account of the research methodology, and discuss the experimental results comprehensively.

By integrating advanced deep learning models with image processing techniques, this research aims to contribute to more efficient and precise lung cancer diagnostics. The evaluation of these models not only highlights their individual strengths but also offers insights into their applicability in real-world clinical settings. This approach holds promise for enhancing diagnostic accuracy and improving patient outcomes in the ongoing fight against lung cancer.

II. REVIEW OF LITERATURE

Article 1 - "Lung Cancer Classification Using Transfer Learning and Deep Convolutional Neural Networks on Chest Radiographs" by Nair et al. (2021): [5]

Methodology: Researchers developed a new method to classify lung cancer using chest X-ray using deep learning and adaptive learning.

Key outcomes: This study demonstrates the effectiveness of adaptive learning in accurately classifying breast cancer based on chest X-ray. This approach shows promise in improving diagnostic accuracy.

Article 2 - "Classification of histopathology Images of Lung Cancer Using Convolutional Neural Network [CNN]" by Neha Baranwal, Preethi Doravari, Renu Kachhoria (2020): [1]

Methodology: The authors developed a convolutional neural network [CNN]-centered strategy to classify lung cancer histopathology images. Their approach includes image preprocessing to improve quality and remove distracting features. The performance of the model is evaluated with indicators to evaluate its accuracy in histopathological classification of lung cancer.

Key Outcomes: The main results of this study demonstrate the effectiveness of convolutional neural networks [CNNs] in classifying lung cancer-related images.

Article 3- "Lung Cancer Detection and Classification Using Transfer Learning and Convolutional Neural Networks" by Jangid et al. (2020):

Methodology: This study uses adaptive learning through refinement of the CNN model, focusing on the detection and classification of lung cancer from CT scan images.

Key outcomes: The study achieved good results with the identification and identification of lung cancer. These results highlight the potential benefits of adaptive learning in improving diagnostic accuracy. Together, these studies demonstrate the successful integration of transfer learning into lung cancer screening, demonstrating the potential to supplement existing models and improve the accuracy and performance of detection. By applying prior knowledge to specific tasks of lung cancer diagnosis, transfer learning has become an effective way to improve diagnosis and promote the advancement of lung cancer diagnosis.

Article 4 - "Histopathologic Oral Cancer Prediction Using Oral Squamous Cell Carcinoma Biopsy Empowered with Transfer Learning" by Atta-Ur Rahman et al. in Sensors (2022):[6]

Methodology: This study involves the use of a deep learning model, first considered as a convolutional neural network [CNN], to learn a global collection of common images. The information obtained from these pre-trained models was adapted and fed into a new CNN model specifically designed for oral squamous cell carcinoma (OSCC) biopsy image classification. Researchers used the OSCC biopsy imaging dataset to train a transformation learning-based CNN to facilitate prediction of the presence and extent of oral cancer in biopsies.

Key Outcomes: The main results of this study show a significant improvement in the prediction of oral cancer accuracy achieved with the modified study method. Using information from the model pre-trained and developed using proprietary OSCC data, the model learns about important patterns and behaviors associated with oral cancer. This method shows great potential for effective oral cancer diagnosis and can support doctors to make a timely and accurate diagnosis.

III. METHODOLOGY

As depicted in Figure 1, the proposed system follows a standard image processing pipeline. This pipeline includes stages such as data collection, preprocessing, segmentation, feature extraction, and classification.

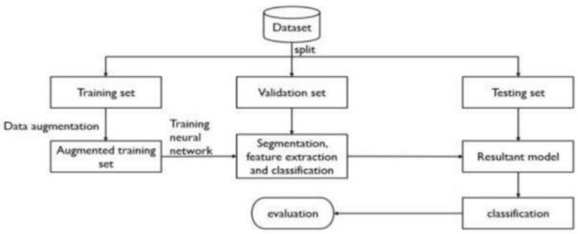


Figure 1: Diagram Depicting the Proposed Methodology

To start with, the dataset was organized into three distinct categories: benign, malignant, and cancer-free. It was then divided into three subsets: training, validation, and testing. Data augmentation techniques were applied to the training set, generating synthetic data to enhance the model training and reduce the risk of overfitting. In the next phase, the convolutional layers of the transfer learning models were used for automatic segmentation and feature extraction. Additionally, a classifier was integrated into a fully connected neural network, which included a dense layer. The SoftMax activation function was utilized in the final layer.

Dataset Collection:
The dataset consists of 1,500 CT scan slices obtained from 110 lung cancer patients at various stages. It includes three specific categories: benign, malignant, and cancer-free cases.

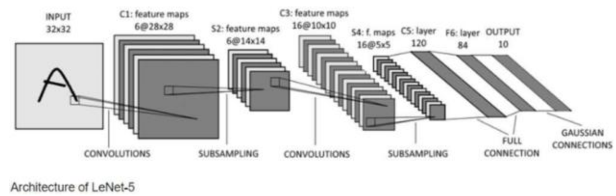
Benign Cases Malignant Cases Normal Cases

Figure 2: Varieties of Images within the Dataset

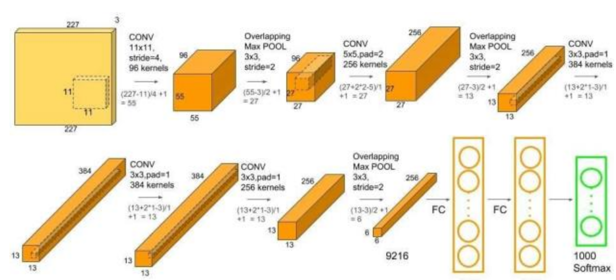
Data Augmentation: Data augmentation involves creating extra training examples from an existing dataset. This approach increases the size of the training data without the need for acquiring new datasets. Importantly, the network processes these augmented images as if they were separate and unique samples.

In this proposed model, a comparative and comprehensive study is conducted on Transfer Learning Model Architectures, including LeNet, Alex Net, Google Net, and VGG19.

LeNet:
LeNet is an early pre-trained model known for its structure, which includes two sets of convolutional layers followed by average pooling layers. This is followed by a flattening layer, and then two fully connected layers, with the final output being classified by a SoftMax layer.

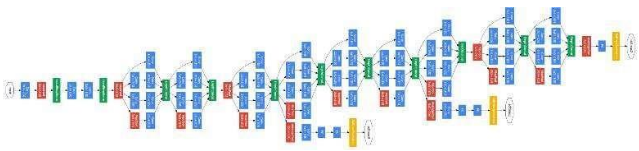


Alex Net:
AlexNet was among the first convolutional neural networks to leverage GPU acceleration for enhanced performance. Its architecture includes five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and a final SoftMax layer. Each convolutional layer utilizes filters and the ReLU activation function, while the pooling layers perform max pooling operations.
The input size is constrained by the fully connected layers, with the standard input dimensions often cited as 224x224x3, although due to padding, the effective dimensions are 227x227x3. AlexNet has approximately 60 million parameters in total.



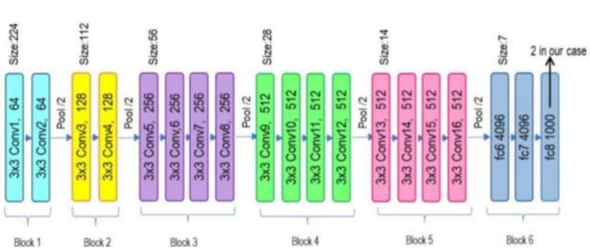
Google Net:

The GoogleNet architecture is characterized by its depth of 22 layers and includes a total of 9 inception modules arranged sequentially. These modules connect to a global average pooling layer at their conclusion. Trained on the ImageNet dataset, GoogleNet excels in classifying images into 1,000 categories, including objects such as keyboards, mice, pencils, and various animals. The network is designed to capture diverse feature representations for a wide range of images. Pre-trained models of GoogleNet use an input size of 224x224 pixels. A key feature of GoogleNet is its efficiency, with a parameter count of approximately 5 million, which is about 12 times fewer than the parameter count of AlexNet.



VGG19:

The VGG19 architecture consists of 19 layers, including 16 convolutional layers, 3 fully connected layers, and 5 max-pooling layers, with a final SoftMax layer for classification. It processes images of size 224 × 224 pixels with 3 color channels, after normalizing by subtracting the mean RGB value. The convolutional layers use a small kernel size of 3 × 3 with 1-pixel padding and a stride of 1. The network incorporates 5 max-pooling layers with a 2 × 2 kernel size and a stride of 2. To introduce non-linearity and improve both classification performance and computational efficiency, the Rectified Linear Unit (ReLU) activation function is used, replacing tanh or sigmoid functions. The network also includes three fully connected layers: the first two with 4096 units each, followed by a final layer with 1000 units for the 1000-way ILSVRC classification. The architecture ends with a SoftMax function to produce the final classification output.



The graph displays the training and validation accuracy along with the training and validation loss over multiple epochs. It clearly shows a steady increase in training accuracy as the number of epochs progresses. This improvement in accuracy is accompanied by a consistent reduction in loss values throughout the training phase.

LeNet

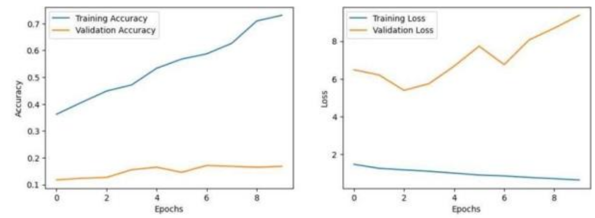


Figure 3.1: Accuracy and Loss for Training and Validation Sets of LeNet Over 10 Epochs

AlexNet

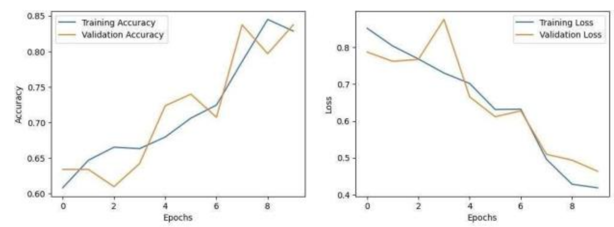


Figure 3.2: Training and Validation Set Accuracy and Loss for AlexNet Across 10 Epochs

GoogleNet

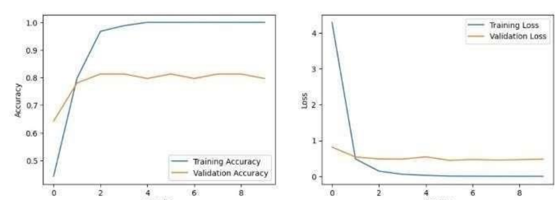


Figure 3.3: Training and Validation Set Accuracy and Loss for GoogleNet Across 10 Epochs

VGG19

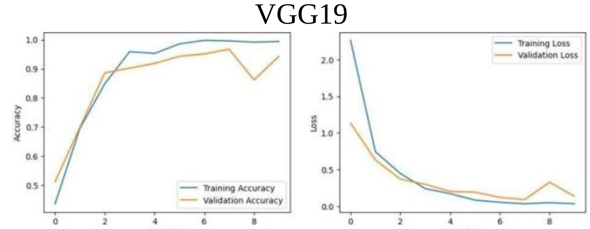


Figure 3.4: Accuracy and Loss for Training and Validation Sets of VGG19 Over 10 Epochs

III. Results and Analysis

Performance metrics derived from the confusion matrix are used to evaluate the effectiveness of these models. These metrics include accuracy, precision, recall, and F1-score. Figures 10.1 – 10.5 illustrate the confusion matrix, which forms the basis for model assessment. In this matrix, True Positives (TP) represent cases where the predicted values match the actual values. True Negatives (TN) refer to cases where all column and row totals, excluding the class being evaluated, are correct. False Positives (FP) are the total values in a column that do not match the True Positives, while False Negatives (FN) are the total values in a row that do not match the True Positives.

LeNET

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Confusion Matrix:
[[ 0 15  0  0 15  8 13]
 [ 0 53  0  0  0  1  0]
 [ 0 42  0  0 47  4 27]
 [ 0 36  0  0 30  5 19]
 [ 0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0]]
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Figure 4.1: Confusion Matrix for LeNet

AlexNet

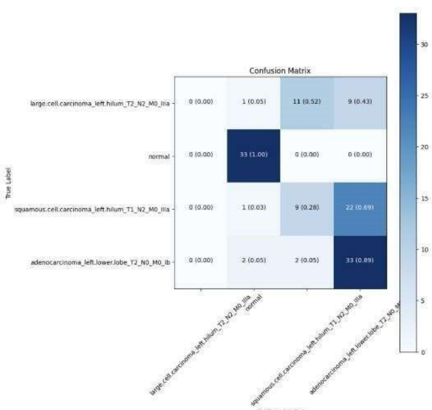

Figure 4.2: Confusion Matrix of AlexNet

GoogleNet

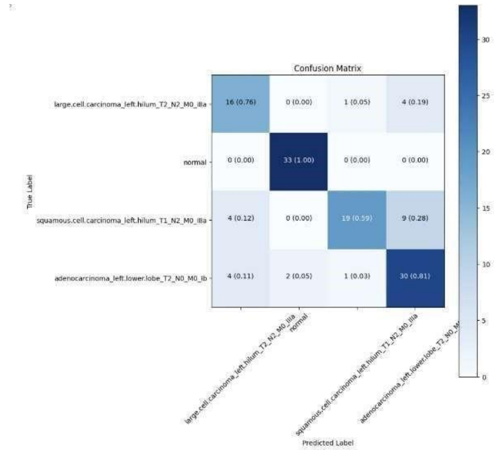

Figure 4.3: Confusion Matrix for GoogleNet

VGG19

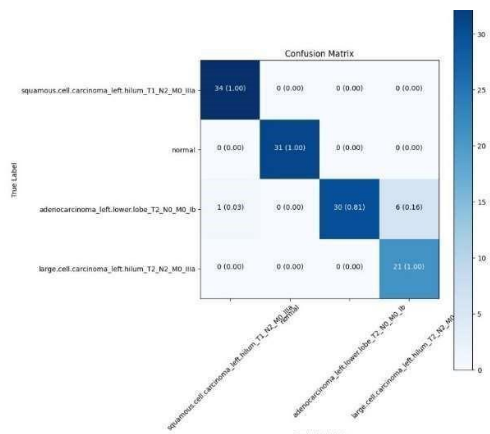

Figure 4.4: Confusion Matrix of VGG19

Figure 5 displays the classification reports for all four architectures.

	Accuracy	Precision	Recall	F1-score
LeNet	0.58	0.06	0.17	0.09
AlexNet	0.72	0.09	0.25	0.13
GoogleNet	0.829	0.09	0.28	0.138
VGG19	0.927	0.09	0.30	0.14

Figure 5: Classification Reports and Metrics for Four Models

The F1-score is a pivotal evaluation metric gauging a model's accuracy. It amalgamates precision and recall scores, offering a comprehensive assessment. A model boasting a higher F1-score is deemed favorable. As indicated in our report, VGG19 emerges with the highest F1-score in comparison to the other architectures. Consequently, VGG19 stands out as the prime candidate for implementing this system.

IV. Conclusion

This study conducted a comparative evaluation of different transfer learning architectures to identify the specific type of lung cancer in patients. The accuracy rates for LeNet, AlexNet, GoogleNet, and VGG19 were recorded as 59%, 72%, 82.9%, and 92.7%, respectively. Among these pre-trained models, VGG19 proved to be the most effective, achieving an impressive accuracy of 92.7%. It is important to note that the current model evaluates only a single CT scan slice. For more effective lung cancer detection, a thorough analysis of the entire lung is necessary. Future research in this field should focus on comprehensive lung evaluations from multiple angles, with the potential application of 3D convolutional neural networks (CNNs) offering a promising approach.

V. References

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