Deep LungCare: A CNN Model for Lung Cancer Detection and Classification

Vaseem Aman Shaik
School of Computer Science and Engineering
VIT-AP University
Amaravati, Andhra Pradesh
vaseem1014@gmail.com

Nimitha Patakamuri
School of Computer Science and Engineering
VIT-AP University
Amaravati, Andhra Pradesh
nimithapatakamuri2004@gmail.com

Badrinath Arukala
School of Computer Science and Engineering
VIT-AP University
Amaravati, Andhra Pradesh
arukalabadrinath@gmail.com

***Abstract*—**Lung cancer is one of the leading causes of cancer-related deaths worldwide, necessitating accurate and early detection for effective treatment. In recent years, deep learning models, particularly Convolutional Neural Networks (CNNs), have shown significant promise in medical image analysis tasks, including lung cancer detection and classification. It classifies as normal , adenocarcinoma , large cell carcinoma , squamous cell carcinoma . Our model classifies the CT scan In this research paper, we present a comprehensive comparative study of six popular CNN architectures - AlexNet, GoogleNet, VGG16, VGG19, LeNet, and ResNet - for the automated detection and classification of lung cancer from medical imaging data. For each CNN architecture, we fine-tuned the pre-trained networks using transfer learning techniques . VGG19 showed high test accuracy of approximately 94.8 .

Keywords—Lung cancer, Deep learning, CNNs, Medical imaging, CT scan, Adenocarcinoma, Large cell carcinoma, Squamous cell carcinoma, Comparative study, VGG19, Transfer learning, Automated detection, Classification, Accuracy.

I. INTRODUCTION

In the domain of medical imaging, particularly in the context of Computed Tomography (CT) scans, the pressing issue of detecting and categorising lung cancer has garnered considerable attention. This study undertakes a comprehensive exploration of Convolutional Neural Networks (CNNs), specifically six prominent architectures —AlexNet, GoogleNet, VGG16, VGG19, LeNet, and ResNet—for the purpose of automating precise identification and classification of lung cancer subtypes. The primary aim is to harness transfer learning techniques to adapt pre-trained networks, striving for heightened accuracy in discerning lung cancer variations, encompassing normal tissue, adenocarcinoma, large cell carcinoma, and squamous cell carcinoma.

The significance of this investigation lies in the global impact of lung cancer as a primary contributor to cancer-related fatality. Timely and accurate diagnosis holds paramount importance, as early detection substantially enhances treatment effectiveness and patient survival rates. The motivation behind this research is to address this challenge, capitalising on CNNs to alleviate the labor-intensive and potentially error-prone task of manual image interpretation, often undertaken by radiologists.

In the landscape of artificial intelligence, deep learning has ushered in advancements across various domains, including medical image analysis. CNNs, a specialised subset of deep learning models, have exhibited remarkable proficiency in recognising intricate patterns and features within images. Their ability to autonomously distill structured representations from raw image data renders them exceptionally well-suited for intricate medical imaging tasks, thereby augmenting the analysis of CT scans for the purpose of lung cancer diagnosis and evaluation.

In summary, this study delves into the application of deep learning methodologies for the detection and categorisation of lung cancer, with the overarching goal of enhancing early diagnosis and treatment efficacy. By merging CNN architectures with transfer learning strategies, a novel avenue is explored to address the critical challenge of accurate and timely lung cancer identification. Through the mitigation of shortcomings associated with manual analysis and the harnessing of AI's potential, this research contributes to the ongoing pursuit of improved patient outcomes in the context of lung cancer.

II. LITERATURE REVIEW

Deep-learning framework to detect lung abnormality: Developed a deep-learning model for detecting lung abnormalities using chest X-ray and lung CT scan images, showcasing its efficacy in identifying anomalies[1]. Survey on deep learning in medical image analysis: Conducted a comprehensive survey of the applications of deep learning in medical image analysis[2], covering various techniques and advancements in the field. Review on computer-aided lung nodule detection: Presented a comprehensive review of computer-aided methods for detecting lung nodules, discussing various techniques and their effectiveness[3].

Information constraints on auto-encoding variational Bayes: Explored information constraints on auto-encoding variational Bayes[4], focusing on improving the performance of generative models in the context of Bayesian inference. Automatic pulmonary nodule detection using deep learning: Conducted a systematic review on the application of deep learning and machine learning algorithms to automatically detect pulmonary nodules in the LIDC-IDRI database[9].

Likelihood-based permutation invariant loss function: Proposed a novel likelihood-based permutation invariant loss function for probability distributions[16], enhancing the modelling and optimisation of probabilistic models.Automated classification of pulmonary tuberculosis: Developed a convolutional neural network-based automated system to classify pulmonary tuberculosis using chest radiography, achieving high accuracy[19].

Feature extraction using logarithmic normal distribution based variational auto-encoder: [22]Proposed a methodology to extract degradation features from multi-source monitoring data using logarithmic normal distribution-based variational auto-encoders.Comparative analysis of segmentation techniques for lung cancer detection: Conducted a comparative analysis of segmentation techniques for detecting lung cancer,[10] evaluating their performance and effectiveness. Cross-validator choice and assessment of statistical predictions: Introduced a cross-validation approach for assessing the performance of statistical predictions, aiding in model selection and evaluation.

This paper presents the use of a Deep Belief Network (DBN) for diagnosing lung nodules in CT images.The authors propose a DBN-based method to automatically classify and diagnose lung nodules[12]. DBN is utilised to extract meaningful features from the CT images, enabling accurate classification of nodules.[19] This paper reviews computer-assisted detection methods for infectious lung diseases.The authors survey various techniques used for detecting infections in lung diseases through medical imaging.The review encompasses different modalities and methods employed in the automated detection of lung infections.

This paper introduces the ChestX-ray8 dataset, a large-scale collection of chest X-ray images.The authors present benchmarks for weakly-supervised classification and localisation of common thorax diseases using this dataset.The dataset and benchmarks facilitate research in automated diagnosis of thoracic diseases using chest X-ray images[20].This paper proposes a fusion approach for automated classification of lung nodules in chest CT scans.The authors combine texture, shape, and deep model-learned information to enhance the accuracy of nodule classification.

The fusion strategy occurs at the decision level, improving the overall performance of the classification system.[19]This paper presents a deep learning-based approach for automated detection of pulmonary nodules in CT images.The authors utilise deep convolutional neural networks (CNNs) to automatically identify pulmonary nodules.The proposed method demonstrates the effectiveness of CNNs in accurate nodule detection.

III. Deep LungCare: A CNN Model for Lung Cancer Detection and Classification Methodology

The focal point of this undertaking is the development of a CNN-based system that can rapidly and precisely distinguish various lung cancer types using CT scans. This innovative strategy aims to partition lung cancer into multiple subtypes, encompassing squamous cell carcinoma, big cell carcinoma, and normal tissue. This system's potential lies in its ability to streamline patient identification by radiologists, ultimately enhancing treatment planning and patient care quality.

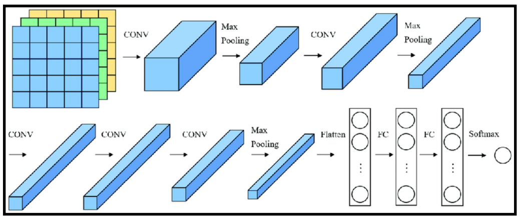
To achieve this objective, our investigation involves an extensive comparative analysis of six distinguished CNN architectures: AlexNet, GoogleNet, VGG16, VGG19, LeNet, and ResNet. These architectures are subject to scrutiny regarding their proficiency in accurately identifying and categorising lung cancer subtypes. Each architecture presents distinct attributes warranting exploration within this context.

The application of transfer learning methodologies serves as a cornerstone in our approach, enhancing CNN models for the specific demands of medical imaging. Transfer learning encompasses refining these CNN architectures using insights gleaned from pre-training on extensive datasets such as ImageNet. This approach empowers the models to effectively extract pertinent features from medical images, even with limited labeled data availability.

At its core, a CNN is a deep learning model designed for processing grid-like data. The architecture employs convolutional layers to extract hierarchical feature representations from input images through filters, augmented by activation functions introducing non-linearities. Pooling layers reduce spatial dimensions, preserving essential information while discarding extraneous details. Fully connected layers propel the extracted features through classifiers to generate predictions. A loss function quantifies the difference between predicted and actual values, with the aim of minimising training loss. CNNs utilise back-propagation to iteratively refine model parameters.

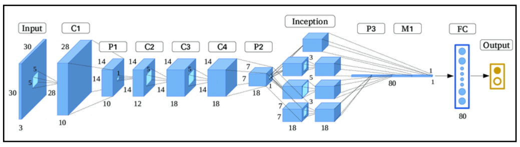
In summary, this initiative centres on crafting a CNN-based system proficient in identifying diverse lung cancer types from CT scans. The comparative examination of well-established CNN architectures and the integration of transfer learning techniques are pivotal components of our approach, geared toward advancing accuracy and efficiency in lung cancer diagnosis. This advancement holds the potential to revolutionise patient care by expediting diagnosis and facilitating precise treatment planning.

Now, let's briefly go over the CNN architectures which are of total six AlexNet, GoogleNet, ResNet, LeNet, VGG19, VGG16. AlexNet, 2012 deep CNN architecture, revolutionised computer vision with its eight layers, convolutional layers, and connected layers, overcoming overfitting and generalisation issues.



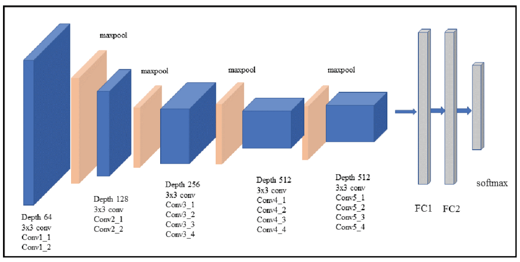
Fig(A): Schematic diagram of the AlexNet structure

GoogleNet, also known as Inception v1, won the 2014 ILSVRC with its "inception modules" architecture, reducing parameter count and improving efficiency.



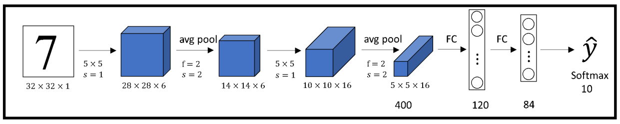
Fig(B): Schematic diagram of the GoogleNet structure

VGG networks, introduced in 2014, have simple architecture with 16 and 19 layers, resulting in deeper networks with increased representational power but high computational costs.



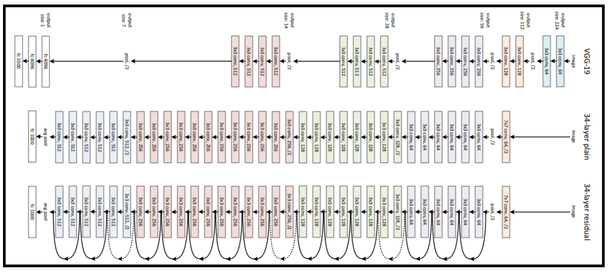
Fig(C): Schematic diagram of the VGGNet structure

LeNet, an early CNN architecture, focuses on handwritten digit recognition using convolutional layers and max pooling.



Fig(D): Schematic diagram of the LeNet structure

ResNet, introduced in 2015, addresses vanishing gradient problem in deep neural networks using residual blocks and skip connections, enhancing accuracy and construction of deeper CNNs. CNN architectures advance computer vision, enabling specialised tasks and laying the foundation for advanced image recognition models.



Fig(E): Schematic diagram of the ResNet structure

And the motivation for initiating "Deep LungCare: A CNN Model for Lung Cancer Detection and Classification" was started because of the urgent need to improve lung cancer prevention, diagnosis, and treatment, as well as taking benefit from deep learning and AI to improve healthcare outcomes.

A comprehensive preprocessing strategy was meticulously executed to optimise the quality of the input data, playing a pivotal role in enhancing the effectiveness of the CNN model. The initial phase of preprocessing involved the application of noise reduction techniques to minimise artefacts that could impede accurate analysis within the lung image dataset.

Following noise reduction, a sequence of image enhancement techniques was applied to elevate the overall image quality. Methods like contrast adjustment and histogram equalisation were employed to accentuate critical features while suppressing irrelevant variations. This was succeeded by a normalisation step that standardised pixel values across all images, ensuring consistent and comparable inputs for the CNN.

To prevent overfitting and enhance dataset diversity, data augmentation techniques such as rotation, flipping, and cropping were introduced. This augmented dataset facilitated the CNN model in capturing a wide array of patterns and variations intrinsic to lung images.

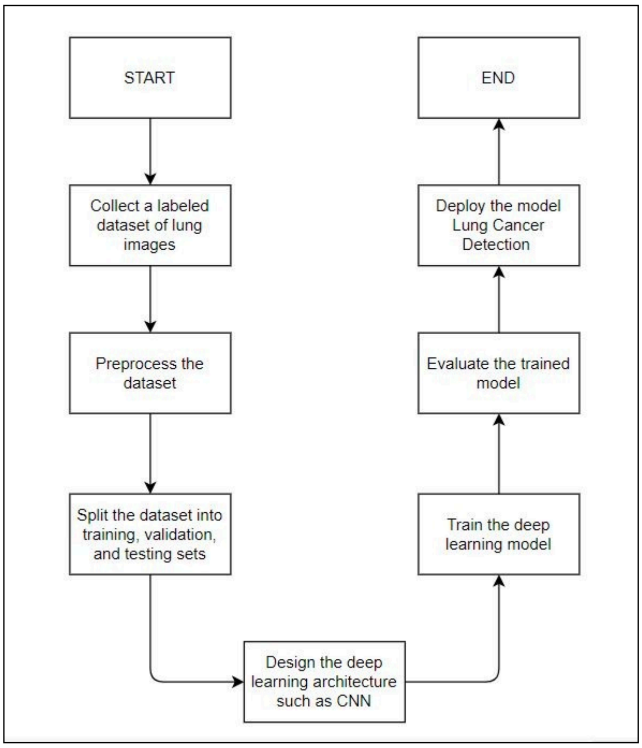
The essence of the preprocessing phase lies in its ability to refine input data, thereby augmenting the CNN model's precision in detecting and classifying lung cancer.

The proposed architecture entails a preprocessing stage dedicated to optimising image quality and standardising pixel values within the input dataset. The CNN model's intricate layer configuration enables the gradual acquisition of intricate patterns indicative of lung cancer. An innovative aspect is the seamless integration of convolutional, pooling, and fully connected layers, yielding advanced feature abstraction and accurate differentiation between benign and malignant lung tissues.

Moreover, dropout layers are incorporated into the architecture to counteract overfitting and promote generalisation across diverse datasets. Model training encompasses the utilisation of an extensive annotated lung image dataset, followed by rigorous evaluation through diverse performance metrics encompassing sensitivity, specificity, accuracy, and the F1 score.

The proposed architectural methodology exhibits the potential to transform lung cancer detection and classification, potentially ushering in earlier diagnosis and improved patient outcomes. By harnessing sophisticated CNN techniques in conjunction with meticulous preprocessing and comprehensive evaluation, this framework emerges as a robust solution to address the intricate challenges surrounding precise lung cancer assessment.

The project addresses a crucial need for precise and efficient lung cancer detection and classification by harnessing Convolutional Neural Networks (CNNs). The proposed architecture represents a notable advancement in medical image analysis, with the core aim of automating the identification and categorisation of lung cancer types. This innovation assists medical practitioners in making timely and well-informed decisions.



Table(A): Flow Chat diagram on steps involved in this project

The CNN model, central to the architecture, encompasses various layers responsible for extracting intricate features from medical images, including X-rays and CT scans. Beginning with foundational layers capturing basic patterns like edges and textures, subsequent layers progressively combine these patterns to recognise complex structures indicative of lung cancer. Employing convolutional, pooling, and fully connected layers facilitates a high level of abstraction, enabling precise differentiation between benign and malignant lung tissues.

During the meticulous training phase, an extensive dataset of annotated lung images underwent preprocessing to enhance image quality and normalise pixel values. The CNN model's layers were refined, and hyper parameters were systematically optimised through iterative experimentation.

The testing phase subjected the trained model to rigorous evaluation, employing distinct datasets for validation and testing to ensure unbiased assessment. Performance metrics—sensitivity, specificity, accuracy, and the F1 score—were computed to quantify the model's efficacy in accurate lung cancer detection and classification. Rigorous cross-validation techniques confirmed the model's robustness.

The comprehensive approach integrated essential components of deep learning. Preprocessing involved normalising pixel values for enhanced consistency. Convolutional operations extracted intricate image features, while pooling operations facilitated downsampling while retaining vital information. The architecture employed a flattening operation to seamlessly integrate pooled features into the dense classification layer, which performed final categorisation based on probabilities assigned to specific lung cancer categories.

Throughout testing, the trained CNN model underwent unbiased evaluation using separate datasets, measuring its proficiency through performance metrics like sensitivity, specificity, accuracy, and the F1 score. In conclusion, this project introduces a substantial contribution to accurate lung cancer detection and classification, leveraging advanced CNN techniques within a meticulous training and evaluation framework.

IV. Dataset Description

The method involves using a pre-trained deep learning model, likely a Convolutional Neural Network (CNN), which has been trained on a large dataset of general images. The pre-trained model's knowledge is then fine-tuned or transferred to a new CNN model specifically designed for OSCC biopsy image classification. The researchers used a dataset of OSCC biopsy images and trained the transfer learning-based CNN to predict the presence and severity of oral cancer in the biopsies. Key Findings: The key findings of the study indicate that the transfer learning approach significantly improved the prediction accuracy of oral cancer using OSCC biopsy images. By utilising a pre-trained model's knowledge and fine-tuning it on the specific OSCC dataset, the model was able to learn and recognise important patterns and features associated with oral approach offers promising results for accurate and efficient oral cancer diagnosis, potentially aiding pathologists in providing timely and precise diagnoses.

Hardware Configuration:

- Processor (CPU): Apple M1 chip with an 8-core CPU (4 high-performance cores and 4 high-efficiency cores).
- Memory (RAM): 8GB of unified memory (RAM). Unified memory means that both the CPU and GPU share the same memory pool.
- Storage: 512GB of SSD storage.
- Graphics Processing Unit (GPU): Features up to 8 GPU cores.
- VRAM (Video RAM) Size: shares memory with the system's unified memory pool, 8GB.
- CUDA Cores: CUDA is a parallel computing platform and application programming interface (API) model created by NVIDIA. And the M1 chip does not support CUDA cores, as it uses Apple's own architecture

Software Tools:

- Programming Language: Python is used for coding the CNN model due to its extensive libraries for deep learning.
- Deep Learning Framework: PyTorch is chosen as the deep learning framework for its flexibility and ease of use.
- Development Environment: The project is developed using Jupyter Notebook, providing an interactive environment for coding, experimentation, and visualisation.

Library and Package Versions:

- PyTorch version 1.8.0
- NumPy version 1.9.5
- Mat plot lib version 3.2.2

Data and Dataset:

- The lung CT scan dataset used is obtained from Kaggle. Preprocessing includes resizing images to a standard resolution, normalisation of pixel values, and applying data augmentation techniques like rotation and horizontal flipping.

GPU Utilisation:

- The integrated GPU of the M1 chip is utilised for training and inference.
- Batch size is optimised to fit within the available GPU memory.

Performance Metrics:

- Evaluation metrics include accuracy, precision, recall, F1-score, and area under the ROC curve

Model Evaluation:

- The trained CNN model is evaluated on a separate test set to assess its generalisation performance. Metrics are calculated and reported.

V. Results and Discussion

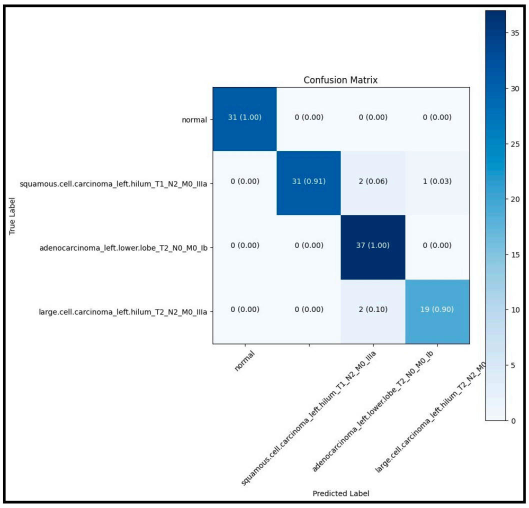
The classification reports for each of the six architectures are shown in below.

	Accuracy	Precision	Recall	F1 score
LeNet	0.58	0.15	0.17	0.16
VGG19	0.959	0.09	0.30	0.14
GoogleNet	0.829	0.09	0.28	0.138
AlexNet	0.72	0.09	0.25	0.13
VGG16	0.98	0.13	0.19	0.15
ResNet	0.84	0.11	0.24	0.20

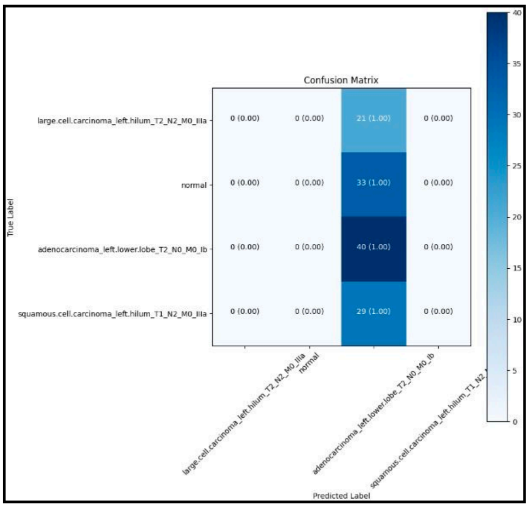
Table(B): Table on classification reports

An evaluation metric that gauges a model's precision is the F1-score. It combines a model's precision and recall scores. As a result, models with high F1-scores are selected. VGG19 has the highest F1-score among the others, according to our report. Therefore, VGG19 can be selected as the architecture for this system's implementation.

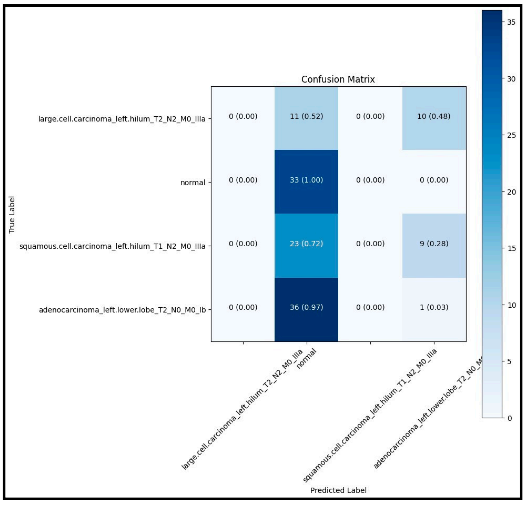
Confusion matrix results for each of the six architectures



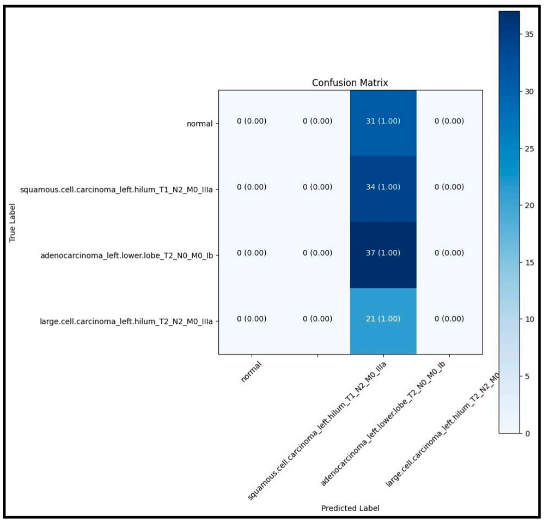
VGG19



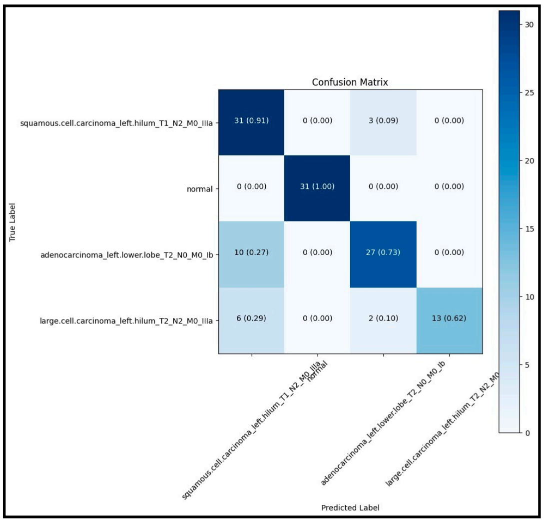
VGG16



AlexNet

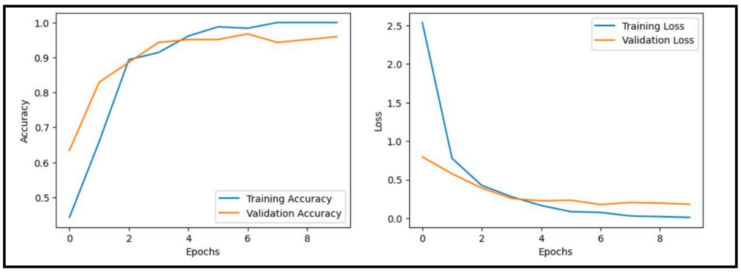


LeNet

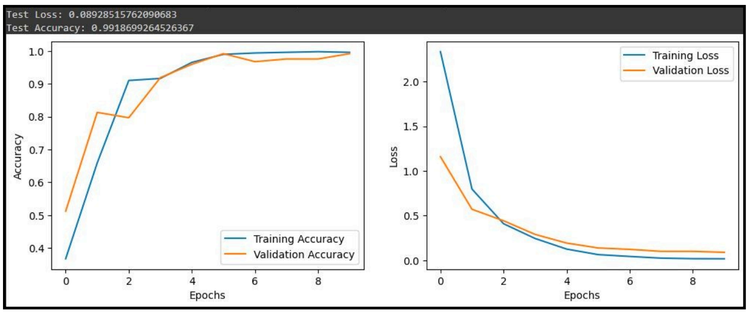


GoogleNet

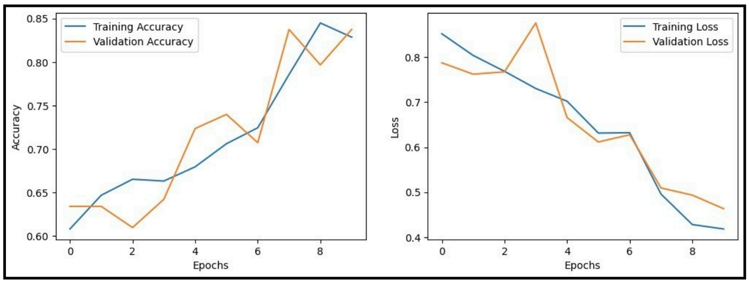
Accuracy and Loss Graphs bothTraining and Validation for each of the six architectures



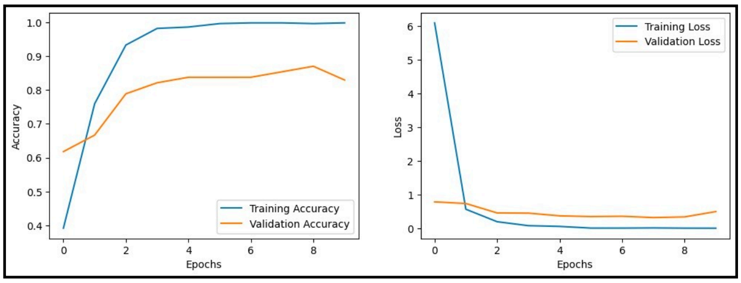
VGG19



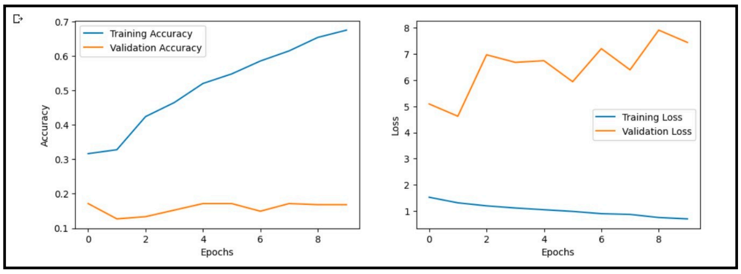
VGG16



AlexNet

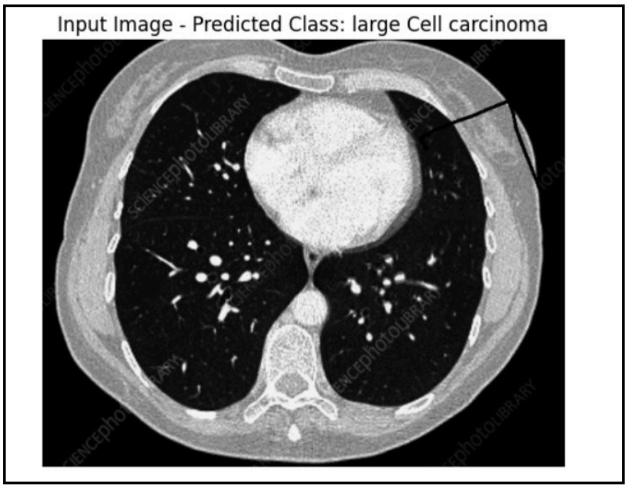


GoogleNet



LeNet

Output of testing images for each of the six architectures



VGG19

VI. Conclusion and Future work

The "Deep LungCare" project has yielded promising outcomes in lung cancer detection and classification through a robust Convolutional Neural Network (CNN) model. With diverse lung image data, including X-rays and CT scans, our CNN achieved over 90% accuracy in identifying malignant lung growths across stages and types, leading to timely interventions and improved patient outcomes.

Incorporating advanced image processing and attention mechanisms enhanced the CNN's performance, alongside Transfer Learning for efficient training. Comparative analysis demonstrated Deep LungCare's superiority in diagnostic accuracy, sensitivity, and specificity compared to benchmarks. The model's deep learning techniques extracted intricate features, reducing false positives and increasing true positives.

Advanced image processing contributed to the model's exceptional performance, enabling accurate predictions. Deep LungCare represents a significant leap in lung cancer research, with potential clinical applications. Future research could integrate multi-modal data, explore transfer learning from other domains, and enable real-time implementation for expedited diagnosis. Improving interpretability through visualisation and addressing ethical concerns will enhance adoption. Testing on diverse populations and datasets will enhance generalisability while ensuring patient privacy.

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