# Deep Learning-Based Lung Cancer Detection and Classification from Medical Images

MSc Research Project
MSc in Data Analytics


Amal Sunny
Student ID: X22169806

School of Computing
National College of Ireland

Supervisor: Harshani Nagahamulla

**National College of Ireland**

**MSc Project Submission Sheet**

**School of Computing**

| | |
|---|---|
| **Student Name:** | Amal Sunny |
| **Student ID:** | x22169806 |
| **Programme:** | Data Analytics |
| **Year:** | 2023 |
| **Module:** | MSc Research Project |
| **Supervisor:** | Harshani Nagahamulla |
| **Submission Due Date:** | 14/12/2023 |
| **Project Title:** | Deep Learning-Based Lung Cancer Detection and Classification from Medical Images |
| **Word Count:** | 9138 |
| **Page Count:** | 23 |

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

| | |
|---|---|
| **Signature:** | Amal Sunny |
| **Date:** | 14th December 2023 |

**PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST**

| | |
|---|---|
| Attach a completed copy of this sheet to each project (including multiple copies) | □ |
| **Attach a Moodle submission receipt of the online project submission,** to each project (including multiple copies). | □ |
| **You must ensure that you retain a HARD COPY of the project**, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer. | □ |

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

| **Office Use Only** | |
|---|---|
| Signature: | |
| Date: | |
| Penalty Applied (if applicable): | |

# Deep Learning-Based Lung Cancer Detection and Classification from Medical Images

Amal Sunny
X22169806

Lung cancer is one of the most common causes of cancer-related deaths, and early detection is critical for effective treatment. However, traditional diagnostic methods that include manual inspection of the medical imaging slides have limitations in their accuracy and can be time-consuming. To overcome these challenges, deep learning approaches like convolutional neural networks (CNN) have shown great potential for providing fast, accurate, and non-invasive diagnostic tools. However, to improve the accuracy and efficiency of these models, a standardised image pre-processing technique is necessary. Such techniques could help reduce the cost and time associated with traditional diagnostic methods. By leveraging the power of deep learning, we can enhance the accuracy of lung cancer diagnosis, reduce the need for invasive tests, and ultimately improve patient outcomes. The empirical evidence from this investigation underscores the superior performance of the InceptionNetV3 model, and VGG19 model, achieving a 84.47%, and 85.84% accuracy rate in lung cancer detection. These findings not only underscore the significance of model selection in deep learning applications but also illuminate the path for further refinements in automated diagnostic technologies.

**Keywords:** ***Lung Cancer Detection, CNN, InceptionNet, DenseNet121, EfficientNet, VGG16, VGG19, Medical Imaging, Automated Diagnostic Systems.***

# 1 Introduction

Lung cancer is the leading cause of cancer-related deaths, and with around 1.8 million deaths in 2020, it is considered to be one of the deadliest diseases prevalent across the globe [1]. The high mortality rate for lung cancer can be associated with the delayed diagnosis of the disease [2]. According to the NLST trial, it is observed that the death rates of Lung Cancer can be significantly reduced through three annual screenings of low-dose Computed Tomography (CT) of high-risk patients. However, with millions of people suffering from the disease, the three-fold images acquired for them put a burden on the healthcare professionals for timely diagnosis of the disease. This makes it necessary to develop systems capable of detecting the presence of lung cancer from medical images and helping healthcare professionals and doctors rapidly diagnose the disease [3].

As noted by Shakeel et al. [4], the reliability of manual methods, significantly when scaled to many cases, is often questionable due to variability in specialist experience and efficiency. This study addresses these shortcomings by implementing automated, deep learning-based approaches. The motivation for exploring deep learning in lung cancer detection arises from the limitations associated with traditional diagnostic methods which often include manual interpretation of X-ray, CT and MRI scans [4]. These interpretations are often time-consuming and tedious and can be prone to human error [5]. Moreover, these traditional detection methods may miss the signs of the early stages of cancer [3].

The application of image processing and computer vision in the medical field, particularly in lung cancer detection, is essential due to its non-invasive analysis and cost-effectiveness compared to conventional methods. Analogous to the advancements observed in healthcare applications by Ahad et al. [6] and Rahane et al. [7], this study recognizes the potential of deep learning technologies in revolutionizing lung cancer diagnostics and classification. This study aims to create an automated, non-invasive system for finding lung cancer that is more accurate and efficient. The study aims to find a more reliable, cost-effective, and scalable way to classify lung cancer using deep learning algorithms on medical images. Inspired by the successful application of deep learning techniques in various fields, such as the detection and classification of breast cancer [8], diabetic retinopathy [9], brain tumour classification [10], this research aims to apply similar methodologies to lung cancer detection and classification. The study will leverage CNN for precise classification and feature extraction from lung images.

This study contributes to the pressing need for improved lung cancer diagnostics by proposing an automated, deep learning-based approach to detect and classify lung cancer from medical images. Recognising the high mortality rate associated with lung cancer, largely due to late diagnosis, and the burden on healthcare professionals caused by the volume of images from annual screenings, this research addresses the critical need for rapid and accurate disease diagnosis.

## 1.1 Research Question

- RQ: *How accurate are deep learning techniques in detecting and classifying Lung Cancer (small and non-small cell) in medical images towards making a computer-aided diagnostic system?*
- Sub-RQ: *How does image pre-processing techniques like image rescaling and data augmentation help in improving the accuracy of the deep learning models?*

## 1.2 Research Objectives

Following are the research objectives of the study that needs to be fulfilled in order to answer the research questions mentioned.
Obj 1: Conduct a thorough literature review of the state-of-the-art system.
Obj 2: Identify the most suitable dataset for conducting the study
Obj 3: Identify the most relevant pre-processing steps and implement them.
Obj 4: Implement and Evaluate a CNN model
Obj 5: Implement and Evaluate different deep learning models through transfer learning such as Inception Net, Efficient Net, Dense Net, VGG16 and VGG19 models.
The rest of the report is structured as below.
The subsequent chapter of Related Work discusses the state-of-the-art of the system followed by the Research Methodology chapter discussing the methods used. The design specification chapter details the architecture of the system. The implementation chapter extends the design chapter by detailing the implementation of the deep learning models in the study. The results of the implementation are then discussed in the following Evaluation chapter, the conclusions of the study are discussed in the Conclusion and Future Work chapter.

# 2 Related Work

This section of the report critically assesses different studies conducted in the field of Lung cancer detection using machine learning methodologies and discusses the current state-of-the-art in lung cancer detection and classification, followed by the methodology and implementation of the study.

## 2.1 Importance of Feature Extraction and Image Pre-Processing in Lung Cancer Detection

Feature extraction plays an important role in the detection of lung cancer as it can recognize abnormalities in the affected area of the lungs. Various features like size of the cancer cells, texture and shape adds to the improved accuracy of cancer detection. This is an important step as it aids in the early detection and treatment in a timely manner to eradicate cancer. The below section gives related work in the field of lung cancer detection using various feature extraction techniques.

In this study [11], CT scan images are used for cancer detection where the images are pre-processed using wrapping and cropping technique and the images are divided into local blocks focusing on the region of interest. Gabor Filter, Histogram of Oriented Gradients (HOG), and Haar Wavelet features are used as feature extractors and ten feature vectors are generated by these processes. The extracted features are trained using SVM, Neural Networks, KNN, Decision Tree, Random Forest, and Naive Bayes for classification of benign and malignant classes and, was found that SVM outperformed all other classifiers by giving a test accuracy of 90% using Haar Wavelet features.

Similar research [20] used CT scans for lung cancer detection where the images were subjected to pre-processing, segmentation, feature extraction, and classification. In the pre-processing phase, the images were converted to grayscale and segmentation was performed to remove the background by using contour method and the cancer area was identified based on the pixels having widest coverage. Relevant features like area, contrast, energy, entropy, homogeneity was extracted from the segmented image by calculating the area value and was classified using SVM classifier which gave an accuracy of 83.33%.

This study [23] utilises Shape-Based, Texture-Based Feature Extraction and Local Binary Pattern (LBP) for feature extraction for lung cancer detection where features are extracted based on mean, median, and entropy. The Shape-Based FETs focuses on mass shape abnormalities, categorising extraction into region and contour-based methods while Texture-Based FET’s analyses spatial texture variations and LBP performs pixel comparisons and generates 8-bit codes, forming a mask for updating LBP values. The SVM model implemented over the LBP features achieved an accuracy of 100%.

Another study [13] aims to classify lung cancer using image processing and KNN (k-Nearest Neighbours). The authors acquired 100 image datasets from 4 subjects with lung damage. The image pre-processing involves noise removal using a median filter, and features such as area, perimeter, and centroid. For segmentation process, manual method of segmentation was carried using tools like ImageJ and Adobe Photoshop CS6 where ImageJ was used to invert colors and convert images to binary format, while Adobe Photoshop was used to remove the background, focusing on the lung area. In the feature extraction process, geometric features were extracted and then classified using KNN which achieved a overall score of 98.15%.

## 2.2 Lung Cancer Detection using Deep Learning Techniques

While feature extraction process have their merits, the process involved in classification of lung cancer is tedious as several manual feature extraction steps must be followed before classification. Also, these methods lack the ability to automatically learn hierarchical representations from data unlike the deep learning models (DL). DL on the other hand, have automatic feature extraction process where the CNN layers can detect and extract relevant features without any additional methods. Conventional lung cancer prediction techniques failed to manage the precision because of the low-quality image that affects the segmentation method. The research [18] introduces a novel CNN called IDNet, which combines features from Inception and DenseNet having Inception-like blocks with dense connections. The methods involve designing two basic blocks, Inception-Dense-A (IDA) and Inception-Dense-B (IDB), which combines direct bypass connections, branch structures, and hybrid activation operations. These blocks form the basis of the IDNet architecture, and the hyper-parameter "k" is introduced to describe the amount of feature maps produced by each block. Additionally, a transition block for compression and three variations of IDNet based on different combinations of IDA and IDB blocks has been present. The models were compared with existing models such as DenseNet and ResNet on various image datasets including CIFAR and ImageNet, showcasing competitive or improved classification accuracy with fewer trainable parameters. The strengths include the innovative hybrid structure and flexibility in responding to object semantic regions, while limitations include the absence of detailed computational efficiency analysis and a comprehensive comparison with other hybrid architectures. This research is effective and efficient in addressing the limitations of existing models and contributes to the exploration of design principles in deep learning (DL). In a similar study [38] DenseNet-121 is applied in the diagnosis of pneumonia and lung cancer. The authors applied the model onto a dataset comprising of 3000 chest X-ray images. Strengths of this method include innovative use of DL to enhance accuracy, but challenges such as data preprocessing complexities are also observed. The review also highlights the application of similar innovative approaches for lung cancer detection from CT scans, emphasizing the need for precise classification methods.

This research [22] aims to address gaps in accurately categorising diseases, promising advancements in medical imaging and improved diagnostic accuracy for both pneumonia and lung cancer. The technique applies a sequential method for the identification of the cancer. Two well-organized classifiers, the CNN and feature-based methodology, have been applied. Authors made use of the Lung-CT Diagnosis Datset for the validation of the model. The CNN classifier is optimised by applying a freshly constructed optimization technique called the enhanced Harris Hawk optimizer. This technique is utilized in the dataset, and the classifier is introduced. The proposed method by the authors achieved an impressive accuracy of 95% with recall and f1-score of as high as 97.1%. The study [12] explores how deep learning is applied to detect cancer from CT scan images, with a specific focus on the EfficientNetB7 model. It emphasizes the importance of transfer learning, particularly in adapting to limited training data. The study successfully used the EfficientNet B7 model to accurately identify lung and colon cancers from LC25000 dataset, achieving an impressive accuracy rate of 98%. While showcasing the potential of deep learning in precise cancer categorization, the review acknowledges challenges such as the need for extensive datasets. Günaydinet al. [14], compared machine learning methods both after pre-processing and without pre-processing where the experimental outcomes show that Artificial Neural Networks gives the best outcomes with 82.43% accuracy after image processing. Wang et al. [15] present a weakly supervised approach in this article for fast and effective classification of the whole slide lung cancer images to overcome pixelwise delineated annotations on Whole slide image (WSIs) as they are time-consuming and tedious, which poses threats in constructing large-scale training information. The COVID-19, has been declared a global pandemic and is expanding quickly. Many affected individuals may be protected from COVID-19 by early detection. Sadly, COVID-19 can be misdiagnosed as lung cancer or pneumonia, which can quickly spread throughout the chest cells and kill a patient. A computed tomography (CT) scan and a chest X- ray are the most widely utilized diagnostic techniques for these three disorders. This research [24] proposes a multi-classification deep learning model to diagnose lung cancer, pneumonia, and COVID-19 using a mix of CT and chest X-ray images. This combination has been employed because a CT scan of the chest is helpful even before symptoms occur and can accurately identify aberrant features found in images, whereas a chest X-ray is less effective in the early stages of the disease. The authors utilised various datasets comprising COVID-19 X-ray and CT images as well as RSNA and SIRM datasets to classify the images under consideration using the model. Using these two kinds of photos, the dataset size will grow, and the accuracy of the classification will rise. The author is of the opinion that there isn't another deep learning model in the literature that makes this decision between these illnesses.

CNN has been proven capable of categorising between malignant and benign tissues on CT scan illustrations. In this research by [16], a deep neural network is designed based on GoogleNet, a pre-trained CNN application. The application of the offered network was verified through a simulation on a pre-processed CT scan image dataset, The Lung Image Database Consortium (LIDC) dataset, and compared with that of several pre-trained CNNs, namely AlexNet, GoogleNet and ResNet50 respectively. The outcomes demonstrate that GoogleNet achieved better classification accuracy than the contrastive networks provided. Bhatia et al. [17], describe a pipeline of pre-processing methods to outline lung regions exposed to cancer and extract features using UNet and ResNet prototypes. The application set is fed into multiple classifiers, viz. XGBoost and Random Forest, and the individual predictions are ensembled to forecast the likelihood of a CT scan being cancerous. The authors used the LIDC-IRDI dataset. The model proposed in the study achieved an accuracy of 84%. This paper [18] explores how deep learning, specifically using the VGG19 model, can be applied to detect cancer from CT scan images. By examining a case study on pneumonia classification that utilizes VGG19 and chest X-ray images, the paper emphasizes the broader applicability of deep learning methods in medical imaging, particularly in the field of cancer detection. Using the model on the CIFAR and ImageNet datasets, the model was validated. Key points discussed in the paper include the introduction of crucial sampling techniques, such as random sampling and undersampling. These techniques play a vital role in obtaining datasets that accurately represent cancer cases. Additionally, the paper delves into the details of the VGG19 architecture, well-known for its effectiveness in classifying images. This architecture serves as a versatile tool for various applications within the realm of deep learning. In the study [23], deep learning has been offered as a promising tool to categorize malignant bumps. They tend to retrospectively validate this research's Lung Cancer Prediction Convolutional Neural Network (LCP-CNN), which was trained on US

screening data on an independent dataset of indeterminate bumps in a European multicentre trial, to rule out benign bumps maintaining a high lung cancer captivity. The LCP- CNN, designed on participants with lung bumps from the US NLST dataset, demonstrated excellent performance on the identification of benign lung bumps in a multi-center external dataset, ruling out malignancy with high accuracy in about one-fifth of the patients with 5−15 mm bumps. According to Hatuwal and Thapa [28], in their study uses CNN to examine squamous cell cancer, adenocarcinoma, and benign tissues and CNN is found to be efficient in determining the best course of treatment and prognosis for lung cancer. Application of the model on the LC25000 dataset achieved an accuracy of over 95% on the dataset. In the study by Zhang et al. [29], to detect pulmonary nodules and lung cancer, computed tomography (CT) was used. This study made use of multi-center and open-source data sets such as LUNA16 and a Kaggle dataset. Based on pathologically and laboratory-proven data, a three-dimensional convolutional neural network (CNN) was designed to recognize lung nodules and classify them as benign or malignant disorders. The model implemented in the stud achieved an impressive accuracy of 92%.
According to [41] early diagnosis of the lung cancer can be performed attributed to computer aided diagnosis techniques. The authors treated the lung cancer detection as multiple instances learning problem. They utilised radiomics data obtained from the LIDC-IDRI dataset for training attention-based LSTM model through the management of class imbalance. Their method achieved an accuracy of around 81% for the detection of the lung cancer from the radiomics features extracted from the lung cancer CT images.
Authors of study [42] utilised histopathological images for the detection of non-small scale lung cancer. Using the the Cancer Genome Atlas (TGCA) dataset has been used by the authors after applying immunohistochemistry techniques improving the colours in the dataset images. This study achieved an impressive accuracy of over 97% in detection of the lung cancer.
Study [43] used deep feature extraction techniques to extract features from the LC25000 dataset to which ensemble learning techniques have been applied. Several models, such as VGG16, VGG19, DenseNet169 and DenseNet201, have been used to extract the deep features from the dataset histopathological images. The features are then supplied to machine learning models such as random forest, support vector machine, logistic regression, multilayer perceptron, extreme gradient boosting and LightGBM models. Their approach achieved the highest accuracy of 97.67% for the SVM and MLP models.
Similarly, a study [44] investigated 888 samples from the LIDC-IDRI dataset to test the different machine-learning models for the early diagnosis of lung cancer from CT images. They proposed a deep learning-assisted SVM model to classify the images. Their model achieved an accuracy of 94% in detection of the lung cancer.
A study [45] developed and validated deep learning model using image segmentation method to detect lung cancer from chest radiographs. The model was trained on an acquired dataset consisting of 629 radiographs and was tested on the test data of 151 radiographs. The model achieved a sensitivity of 0.73.

**Table 1: Summary of existing techniques for lung cancer detection**

| Author | Method Used | Accuracy | Data Set |
|---|---|---|---|
| **Shakeel et al. [4]** | Optimized image processing and machine learning for lung cancer detection | 96.2% | Cancer imaging archive (CIA) dataset |

| | | | |
|---|---|---|---|
| **Asuntha & Srinivasan [5]** | Deep learning methods with Fuzzy Particle Swarm Optimization (FPSO) for lung nodule detection | 94.97% | Collected from a Hospital in India |
| **Günaydin et al. [14]** | Comparison of machine learning methods for lung cancer detection | 82.43% (ANN with processing), 93.24% (Decision Tree without processing) | Not Specified |
| **Wang et al. [15]** | Weakly supervised approach for WSI classification in lung cancer | 97% | The Cancer Genome Atlas |
| **Sajja et al. [16]** | Deep neural network based on GoogleNet for lung cancer classification on CT scans | 99% | LIDC dataset |
| **Bhatia et al. [17]** | Pipeline of pre-processing methods using UNet and ResNet for lung cancer prediction | 84% | LIDC-IRDI dataset |
| **Guo et al. [22]** | Lung cancer diagnosis system using CNN and enhanced Harris Hawk optimizer | 95.96% | Lung CT Diagnostic Dataset |
| **Heuvelmans et al. [23]** | LCP-CNN trained on US screening data for lung nodule classification | 99% sensitivity | US NLST dataset |
| **Ibrahim et al. [24]** | VGG16 and CNN model for | 98% for VGG16+CNN model | CT and chest X-ray images |
| **Alzubaidi et al., [11]** | SVM + Haar Wavelet features | 90% | Iraq Oncology Centre |
| **Firdaus Q et al.,[20]** | SVM | 83% | Offline image of unknown patients |
| **Firdaus A et al.,[13]** | Manual Segmentation + KNN | 98% | 100 data samples collected from each of 4 subjects |
| **Singh et al., [12]** | EfficientNetB7 | 98% | Not Specified |
| **Shannaer et al.,** | VGG19 | 86% for unbalanced dataset and 94% for balanced dataset | NSL-KDD Dataset |

# Research Gap

Based on the literature review discussed earlier, it is evident that various machine learning and deep learning algorithms have been developed and tested to detect lung cancer from CT images. However, most of these studies evaluated individual classifiers, and there are very few studies that compared different deep learning techniques against each other. Additionally, it can be noted that not many studies have applied the Efficient Net model for detection. Moreover, the studies discussed used a variety of datasets, but the performances of these models were not discussed for most of the datasets. Therefore, there is a need to address this research gap by comparing different deep learning techniques in the identification of lung cancer from CT images.

# Limitations

Issues pertaining to the CT scan picture pre-processing are mentioned in the extensive analysis of the relevant work [35]. This affected the segmentation and classification tasks' accuracy since pre-processing procedures had to deal with the heterogeneity's discrepancies in order to yield consistent results. When data variability was ignored, deep learning models performed worse and pre-processing techniques had more difficulty extracting accurate features and information. Robust techniques for artifact identification and repair are needed in order to reduce the effect of artifacts on upcoming classification and segmentation processes. Deep learning algorithms for lung cancer diagnosis and detection frequently need a large amount of tagged data for training. On the other hand, getting the right annotations for CT scans was a laborious and challenging process.
Deep learning model training and evaluation may be hampered by the lack of labelled data, which would lower performance and generalizability. Moreover, the training process was tainted and biased by the use of different annotation criteria and procedures across datasets. Deep learning models can be computationally expensive, requiring significant processing power for training and inference, especially those based on convolutional neural networks (CNNs).

# 3 Research Methodology

This report section delves into the research methodology where Knowledge Discovery Database (KDD) is adopted to conduct the presented study which starts from data collection, followed by data pre-processing, feature extraction, model implementation and evaluation of results.

The methodology is developed based on a thorough understanding of the background work discussed in the previous section. The experimental design of the study is presented in Figure 1 below. The image dataset undergoes data pre-processing where the images are resized to 256x256 to maintain uniformity and increase the efficiency of the models during the training phase. Image augmentation is also performed where the images are rescaled and the height and width of the images are sifted focusing on the region of interest. These pre-processed images are then trained using various deep learning models like CNN, InceptionNet, DenseNet121, EfficientNet, VGG16 and VGG19 for detection of lung cancer and classifying them into malignant, benign and normal cases. The models are then evaluated based on their test accuracy and the best performing model is highlighted in this study.

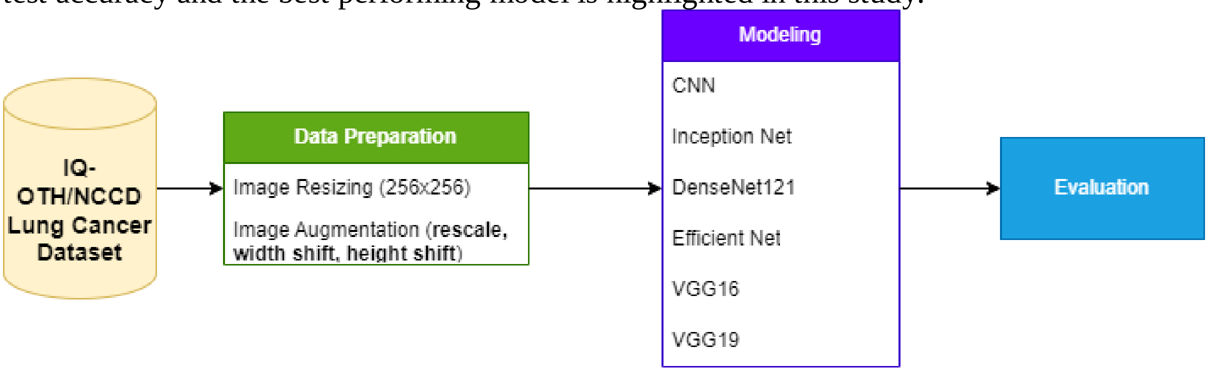



**Figure 1: Experimental Design of the Study**

## 3.1 Data Collection

This study incorporates a comprehensive lung cancer dataset from the Iraq-Oncology Teaching Hospital/National Centre for Cancer Diseases (IQ-OTH/NCCD) [31]. It encompasses computed tomography (CT) scans of individuals diagnosed with lung cancer at varying stages, alongside scans from healthy participants. The dataset, enriched by the expertise of oncologists and radiologists from these centres, comprises 1190 CT scan slices from a total of 110 cases. These cases are systematically classified into three distinct categories: normal, benign, and malignant. The breakdown of these categories includes 40 malignant cases, 15 benign, and 55 normal cases [31]. Figure 2 shows sample images in the dataset. Each CT scan in the dataset includes between 80 and 200 slices, offering diverse perspectives of the human chest. The demographic diversity of the 110 cases encompasses a range of genders, ages, educational backgrounds, areas of residence, and employment statuses.

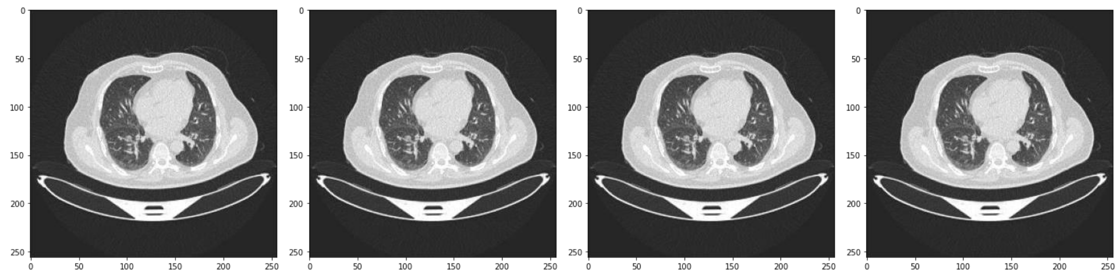


**Figure 2: Sample images from the dataset [31].**

## 3.2 Data Pre-Processing and Feature Extraction

The acquired dataset is then subjected to data pre-processing steps. The dataset consists of images with varying sizes; hence, the images are resized to 256 by 256 size. This ensures uniformity in the data, making it simple for the models to learn over. As mentioned in the previous subsection, the number of images in each class differs. This can make the model biased towards the class in the majority, which should be avoided in machine learning-based data analysis.

In Image segmentation process, image is divided into different segments or regions to separate the region of interest from the rest. At first BGR image is converted to RGB and then the dimensions (width, height, and colour channels) of the image are extracted. This is followed by conversion of RGB to grayscale using cv2.cvtColor(), after that adaptive thresholding is applied to the grayscale image. Adaptive thresholding is a technique that changes the threshold for different regions of the image there by increasing the contrast of images. Then, sorting the area, and selecting the largest contour is performed using contour function. A bounding rectangle is created around this contour, after this, ROI is extracted from the original image. This process is repeated for all lung images using similar steps, finally we will get visualization of segmented region of importance of each image type.

To mitigate the bias, the images are augmented to create additional samples from the existing images through the image augmentation techniques of rescaling, width shift and height shift. This ensured equal samples belonging to each class.

In the process of machine learning, especially when handling image data, the transformation and preprocessing of data assume a vital role [43]. Images are uniformly resized to eliminate size variability and brings consistency to the dataset. To address class imbalances, augmentation techniques such as rescaling and shifting are employed, ensuring a balanced representation of each class and averting model bias. The segmentation of images involves an initial conversion from BGR to RGB, followed by a transition to grayscale, and the application of adaptive thresholding to enhance contrast [43]. This process culminates in the detection of contours and the extraction of the Region of Interest (ROI), directing the focus of the analysis to the most relevant areas. These methods, encompassing resizing, balancing, and segmentation, play a crucial role in refining the input data. Such meticulous preparation of data not only bolsters the model's learning capabilities but also ensures accuracy and impartiality, essential elements in the field of machine learning-based data analysis [41-43].

## 3.3 Data Modeling

Once the data is prepared, it is subjected to various Convolutional Neural Network Architectures listed below.

### 3.3.1 Convolutional Neural Network (CNN)

CNNs are a type of deep learning architecture that is mostly used to process data that has a grid- like structure, like images. They use convolutional layers, which use convolutional filters to extract features from small parts of the input data. This makes them good at tasks like image recognition and classification [32]. The architecture of a typical CNN model is shown in Figure 3 below.

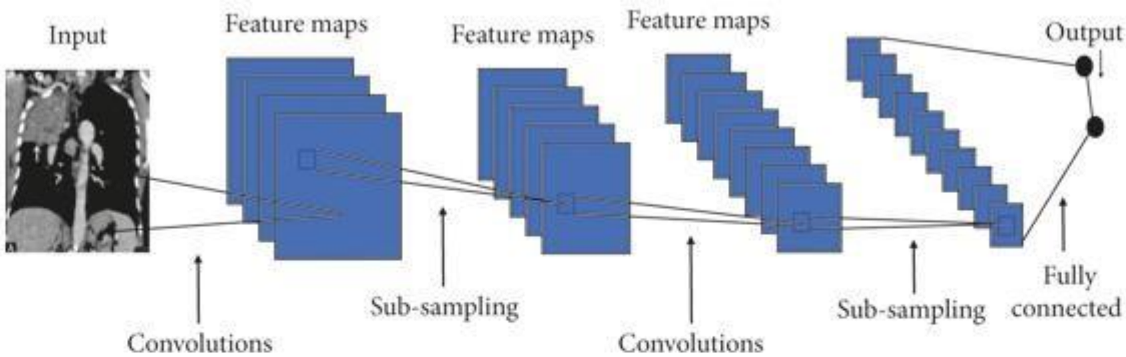



**Figure 3: Architecture of a CNN model [36].**

For the presented study, the CNN model is structured sequentially with three convolutional layers, each followed by max pooling and a dropout of 40% to prevent overfitting. It starts with 128 filters, 64 in the second layer, and 128 in the third. The model includes a flattening layer before two dense layers, with the final layer having three units and a sigmoid activation function, indicating a three-class classification task. Compiled with the 'adam' optimizer and 'categorical_crossentropy' loss function, the model is trained for 10 epochs on a training set with early stopping criterion based on validation accuracy and evaluated using a test set.

### 3.3.2 Inception Net

The Inception Net V3 is a more advanced version of the first Inception Net architecture, which is also called GoogleNet. It is part of the Inception network series. This version was made by Szegedy et al. [33] and includes a number of changes that make it more accurate and efficient. One important improvement is breaking up bigger convolutional kernels into smaller, more efficient ones. This cuts down on the number of parameters and the cost of computing them. Additionally, the network includes extra label smoothing to keep the model from getting too sure of its predictions. This feature helps the model be more useful in real life. The modular approach is still used in Inception Net V3, but the structures have been improved so that the system can learn more complex features with less computer power. This version of the Inception network is widely used for image recognition and classification tasks because it works better and faster than older versions.

The architecture of the Inception Net V3 is depicted in figure 3.4 below. InceptionV3's weights are initialized from ImageNet, and the top layer is modified to adapt the network for a new image classification task. The model is extended by adding a Global Average Pooling 2D layer to minimize overfitting and reduce feature dimensions, followed by a dense network consisting of 1024 neurons with 'relu' activation and an output layer with 3 neurons with 'sigmoid' activation, designed for a three-class classification problem.

During the model compilation, the layers of InceptionV3 are set to non-trainable to retain the pre-trained features, focusing the learning process on the newly added layers. The model employs the Adam optimizer and 'categorical_crossentropy' loss function. To optimize training, an EarlyStopping callback is used to halt training if the validation accuracy does not improve after one epoch, thereby avoiding overfitting. The model trains on shuffled data for a maximum of ten epochs, with performance validation on a separate test dataset. This transfer learning strategy leverages the InceptionV3's pre-learned high-level features, ensuring efficient training with limited data and computational power.

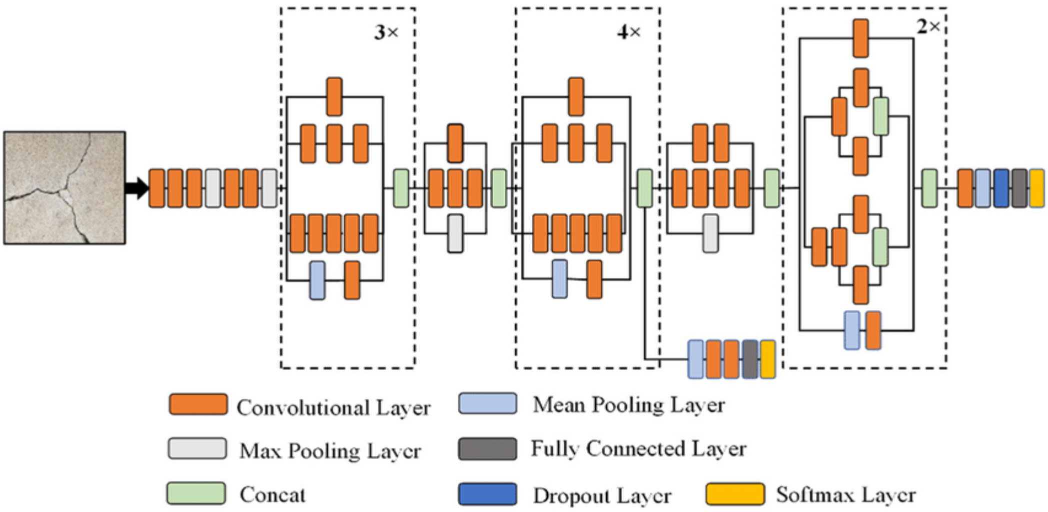



**Figure 4: Inception Net V3 Architecture [39].**

### 3.3.3 DenseNet121

The DenseNet121 model, which is part of the Dense Convolutional Network (DenseNet) family, makes it easier for information to flow through the network and for features to be used more than once. This is possible because of the unique way its layers are connected: each layer is linked to every other layer in a feed-forward way [34].

In regular convolutional networks, each layer is only linked to the next layer. But in DenseNet121, each layer gets extra information from all the layers that came before it and sends its own feature maps to all the layers that come after it. This architecture encourages the reuse of features across the network, which cuts down on the number of parameters and computations needed by a large amount compared to a traditional CNN with the same level of depth [34].
The architecture of the DenseNet121 is shown in Figure 5 below. In order to modify the DenseNet121 model for the purpose of classifying cancer cells, two dense layers and a flattening layer were added. The final output layer utilised a 'tanh' activation function, which is well-suited for multi-class classification. Utilising ImageNet-pre-trained features that are relevant to a vast array of visual recognition tasks, this model operates. The model was trained using early stopping and the 'categorical crossentropy'. Loss and the 'adam' optimizer in order to prevent overfitting. If the validation accuracy did not increase after a certain number of epochs, the model was terminated.

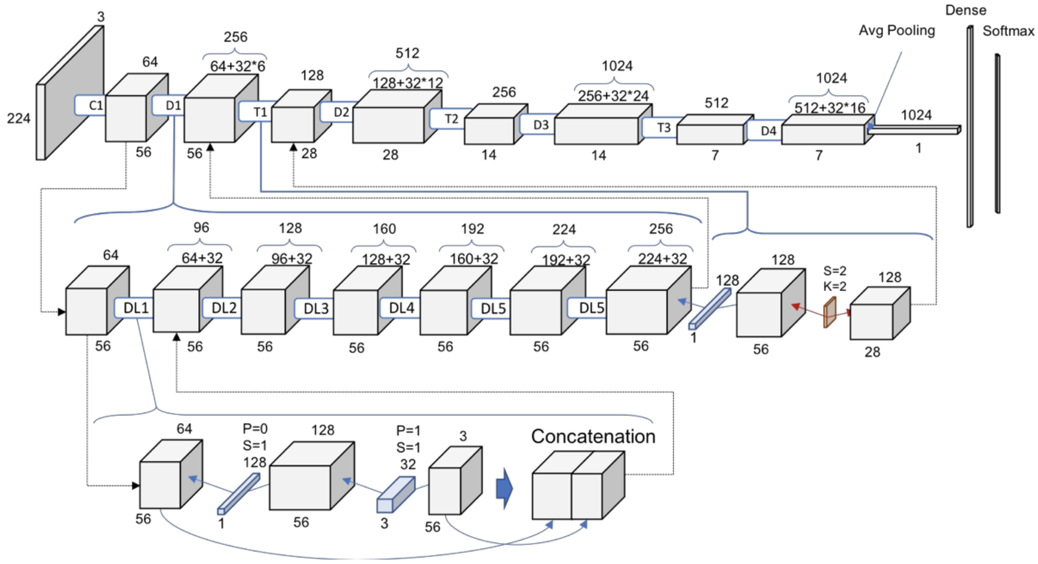


**Figure 5: DenseNet121 Architecture [40].**

### 3.3.4 Efficient Net

Tan and Le introduced EfficientNet in 2019 [21], which is a big step forward in making convolutional neural networks more advanced (CNNs). This model series, which includes EfficientNet-B0 through EfficientNet-B7, gives a methodical and logical way to increase the depth, width, and resolution of CNNs.
An important new idea in EfficientNet is the use of a compound scaling method. Usually, traditional methods scale these dimensions without any reason, which results in networks that are less effective, more complicated, and less fast. EfficientNet, on the other hand, scales each dimension using a set of fixed scaling coefficients that are set by a simple but useful compound coefficient. This makes balanced scaling possible, which improves network performance.
The architecture of the Efficient Net is depicted in Figure 6 below.

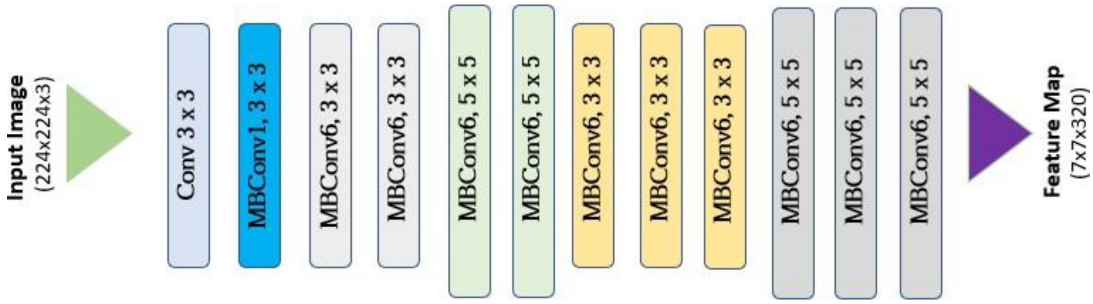



**Figure 6: Efficient Net Architecture [37].**

An additional used model, EfficientNetV2B0, is recognized for its scalability and efficiency. A global average pooling layer was incorporated into this implementation, which was subsequently followed by a series of dense layers and dropout for regularization. The last layers utilized 'sigmoid' activations. The code was produced with the 'adam' optimizer and the 'categorical crossentropy' loss function.

### 3.3.5 VGG16 and VGG19

The deep convolutional neural network VGG16 was created by Simonyan and Zisserman [19]. It is known for having a deep architecture with 16 layers. It has small (3x3) convolutional filters and layers of convolutional filters that are stacked on top of each other. This lets it learn more complex features at each layer. VGG19 is an extension to VGG16. It has 19 layers of architecture that make it deeper. It uses small convolutional filters and many layers, just like VGG16, to find complex patterns in the data.

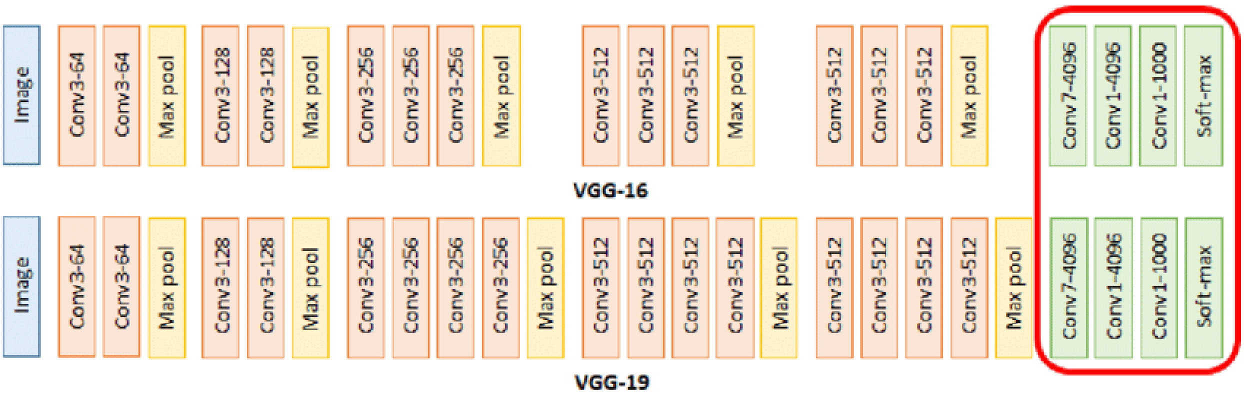



**Figure 7: VGG16 and VGG19 architectures [38].**

The extra layers in VGG19 make it possible to make more complex feature representations but with higher computational complexity [36]. In order to refine the VGG16 model, which is renowned for its depth and simplicity, a flatten layer was incorporated after which a dense layer with 'relu' activation and an output layer modified for three-class classification were added. Significantly, in contrast to the 'adam' optimizer employed in the preceding models, the 'sgd' optimizer was selected for this particular model. During training, the model was prematurely terminated in order to prevent overfitting. Similar refinements were made to VGG19, a variation of VGG16 with extra layers, for the classification job using additional dense layers and 'sigmoid' activation in the output layer. Compilation was performed using the 'sgd' optimizer and 'categorical crossentropy' loss, similar to VGG16. Additionally, early stopping was included to prevent overfitting.

### 3.4 Model Evaluation

The models implemented are evaluated based on the accuracy obtained for the implemented models for both the training set and the validation set. Accuracy measures the ratio of correctly predicted samples to total number of predictions.

# 4 Design Specifications and Implementation

The project design process (depicted in Figure 8) of classification of the lung cancer consists of (i) presentation layer and (ii) business layer. In presentation layer the predictions from the classification models and data exploration are represented in visual form in the Jupyter Notebook. In business layer data selection, data transformation and training of classification models followed by evaluation of models are done.

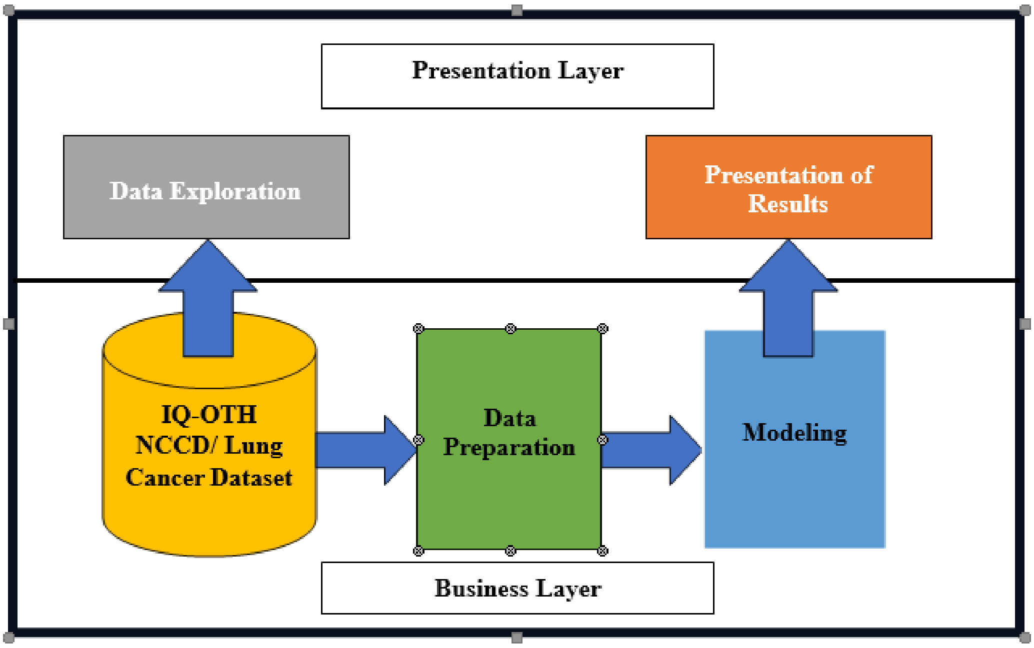



**Figure 8: System Design Process Flow**

The models used in the study are implemented using the ‘Keras’ module of the well-known ‘Tensorflow’ library using the Jupiter Notebook in Anaconda Environment.

# 5 Results and Discussion

## 5.1 Results for CNN model:

The training and testing performance for the CNN model is shown in Figure 9 below. Figure 9(a) depicts the loss curve of the model, whereas Figure 9(b) shows the accuracy curves for the training and validation (testing) set.

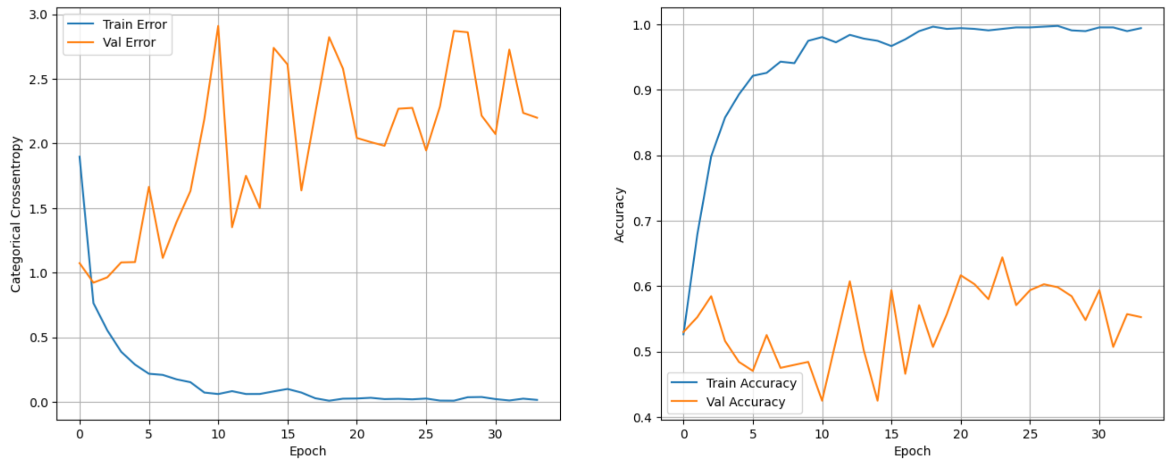



**Figure 9: Model performance for the CNN model**

The training graphs for the Convolutional Neural Network (CNN) model indicate a swift learning from the training data, as seen by the sharp decrease in training error and the steady rise in training accuracy. However, the validation error and accuracy tell a different story, with the error fluctuating considerably and the accuracy lagging behind the training accuracy, suggesting potential overfitting. The model's robustness to new data is questionable due to these inconsistencies, hinting at the need for strategies to improve generalization, such as dropout or regularization, or perhaps a simplification of the model itself.

## 5.2 Results for Inception Net model:

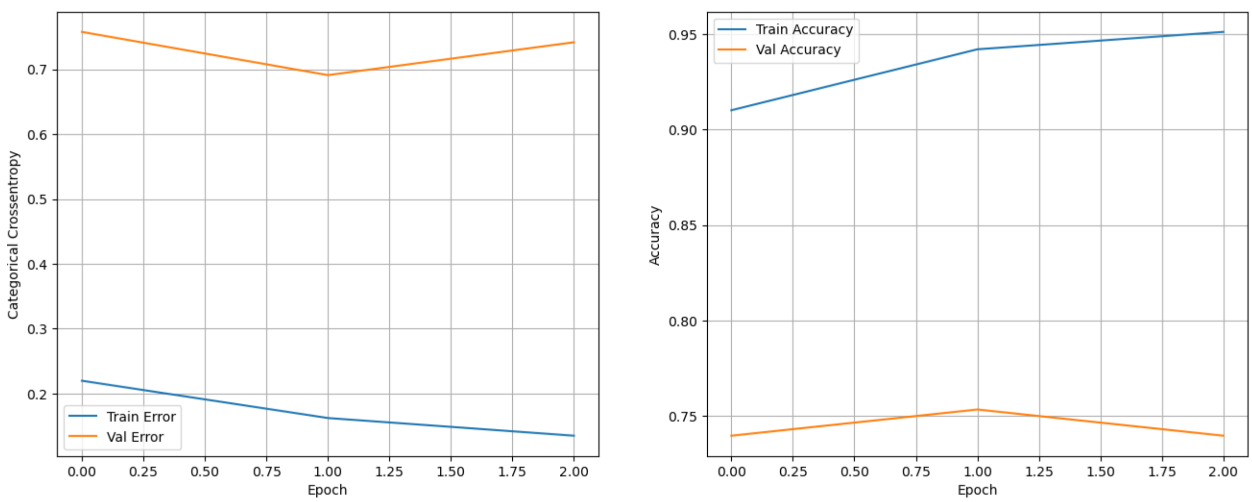



**Fig10: Classification performance of the InceptionNetV3 model**

The training and testing performance for the Inception Net model is shown in Figure 10 below. The graphs presented illustrate the performance of the InceptionNetV3 model during training and validation. The left graph illustrates a declining training error accompanied by a marginally rising validation error. On the other hand, the right graph depicts a high training accuracy approaching 95 percent, but a lower and plateauing validation accuracy around 85 percent. These observed patterns indicate that although the model is efficiently learning the training data, its ability to generalize to the validation data is diminished, which may indicate overfitting. The lack of equal performance between the model's competency on training data and unknown data suggests that other measures, such as data augmentation or regularization, are required to improve generalization.

## 5.3 Results for DenseNet121 model

The graphs that follow in Figure 11 illustrate a steady decline in training loss, which indicates successful learning, however the validation loss remains comparatively constant, which may indicate that the model has not made significant progress beyond a specific threshold on the validation set. Although the accuracy of training improves substantially as epochs go, the accuracy of validation first reaches a plateau, indicating that the model may have overfitted the training data despite having a low dropout rate.

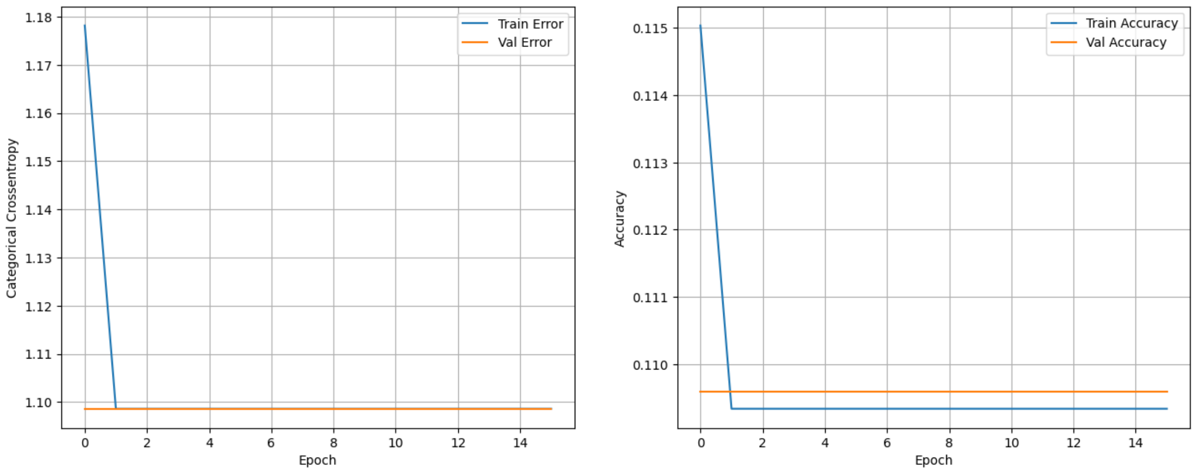



**Figure 11: Performance of the DenseNet121 model**

## 5.4 Results for EfficientNet

As seen in the graphs in Figure 12, the training phase of the model exhibited an atypical pattern characterized by a rise in training loss and a marginal improvement in training accuracy, whilst validation metrics remained constant. The observed performance may suggest potential problems with the configuration of the model or the training data. The lack of anticipated progress during training and the ineffectiveness of the higher dropout rate to improve validation accuracy could indicate underfitting or misalignment with the task.

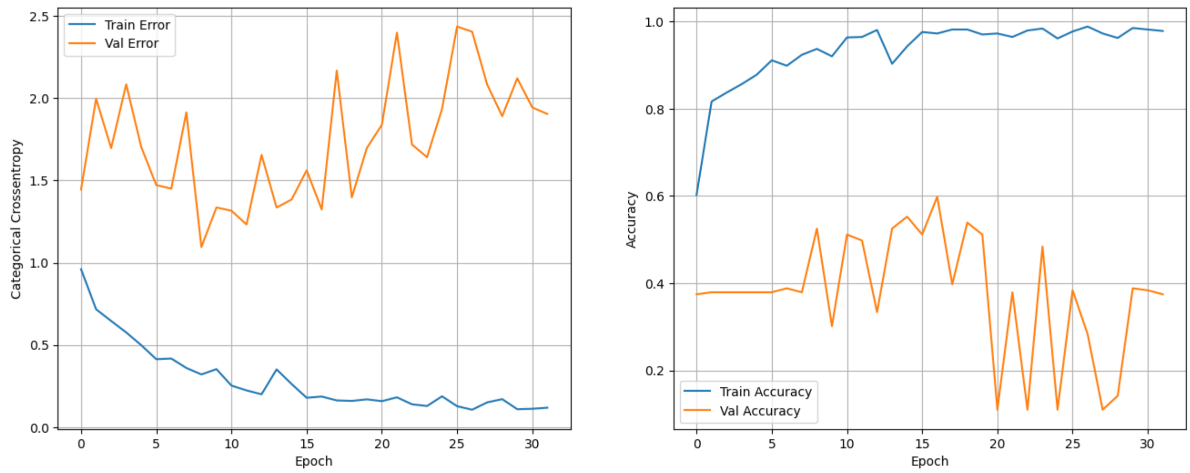
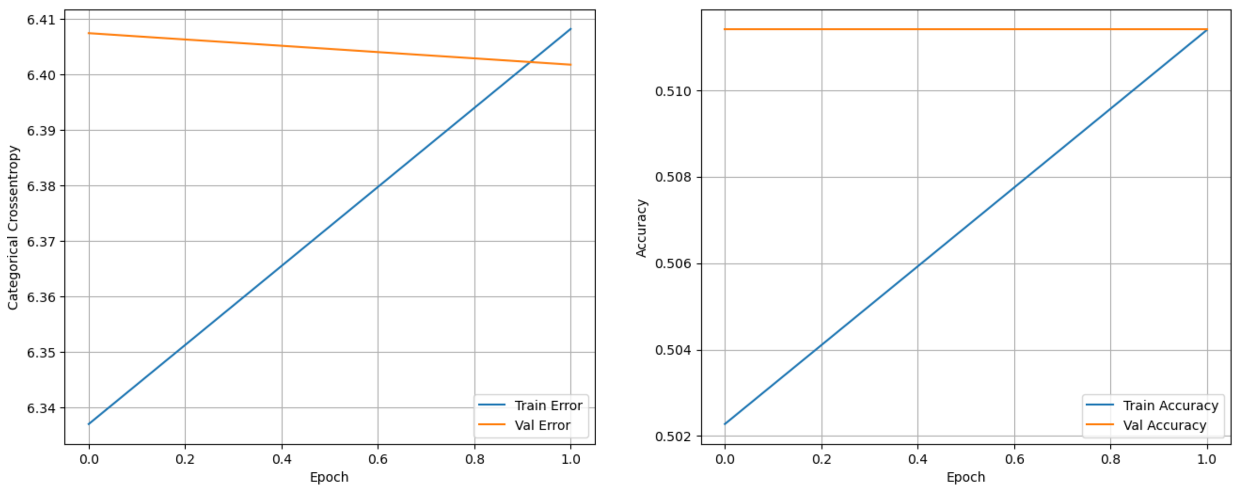



**Figure 12: Performance of the Efficient Net**

## 5.5 Results for VGG16 model

VGG16 exhibited a declining trend in training loss and a consistent ascent in training accuracy as seen in the training graphs. Nevertheless, the validation loss and accuracy exhibited a pretty stagnant trend.
This may suggest that the model's capacity to generalize to unknown data was constrained during the training process, maybe as a result of the model's simplicity in comparison to the task's complexity or inadequate training epochs before early halting. Performance of the model is shown in Figure 12.

**Figure 13: Performance of the VGG16 model**

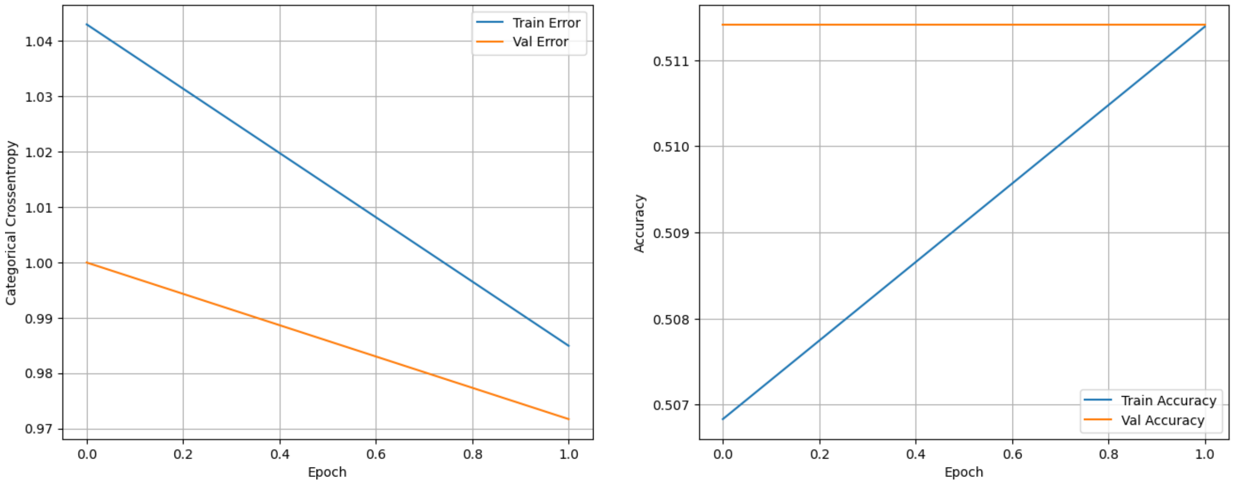



## 5.6 Results for VGG19 model

The performance of the model, as depicted in the graphs in Figure 14, demonstrated a progressive improvement in training accuracy and a significant decrease in training loss. Nevertheless, this progress was not reflected in the validation measures, which remained unchanged across the training epochs. The observed consistency in validation metrics indicates that the model might not have comprehensively exploited the learning capacity of deeper networks such as VGG19 by capturing all the features required for generalization beyond the training data. This is a typical difficulty when employing such networks, which may necessitate more precise tuning and prolonged training periods.

**Figure 14: Performance of the VGG 19 model**

Table 1 below lists the accuracies of the models.




| Models | Accuracy | Loss | Runtime(s) |
|---|---|---|---|
| **CNN** | 55.251139 | 2.198663 | 3264.401217 |
| **InceptionV3** | **84.474885** | 0.908447 | **356.304803** |
| **DenseNet1** | 10.958904 | 1.098612 | 3816.449214 |
| **EfficientNet** | 37.442923 | 1.904712 | 2276.500758 |
| **VGG16** | 10.958904 | 0.000000 | 6394.371368 |
| **VGG19** | **85.844749** | 1.198805 | **16345.081153** |

**Table 1: Comparison of the Models**

CNN, InceptionV3, DenseNet1, EfficientNet, VGG16, and VGG19 models implemented in the study reveal a compelling narrative about their capabilities in processing the lung cancer data, as seen through the lenses of Accuracy, Loss, and Runtime.

Foremost in accuracy are InceptionV3 and VGG19, where high precision in predictions and classifications is observed, with scores of 84.474885 and 85.844749, respectively. This suggests a level of sophistication in their design, adept at handling complex image data. Conversely, DenseNet1 and VGG16 are noted for their lower accuracy, both around 10.95, raising questions about their suitability for the task or potential issues with overfitting or underfitting. Positioned in a middle ground, CNN and EfficientNet are seen as having a balanced capability, though not reaching the higher marks of their counterparts.

The zero-loss value of VGG16 emerges as an intriguing point. Typically, a loss value nearing zero is indicative of overfitting, implying that the model may excel with training data but falter with new, unseen data. In contrast, moderate loss values are seen in InceptionV3 and VGG19, correlating with their high accuracy and suggesting a well-managed learning process.

Regarding runtime, VGG19 is observed to have the longest, indicating a more complex and computationally intensive architecture. On the other hand, InceptionV3 is characterized by its efficiency, completing tasks rapidly and demonstrating an ability to process data swiftly. The varying runtimes of other models like DenseNet1, CNN, and VGG16 reflect their distinct architectural complexities and computational demands.
In summary, the performances of these models underscore the importance of a balance between accuracy, loss, and computational efficiency in machine learning. The accuracy of InceptionV3 and VGG19 stands out, yet the high computational demand of VGG19 warrants consideration. The zero-loss value of VGG16 is unusual and raises practical applicability concerns. CNN and EfficientNet, with moderate performances, suggest areas for potential improvement. Finally, the low accuracy of DenseNet1 highlights the significance of appropriate model selection and tuning for specific tasks.
Figure 15 below shows the graphical comparison of the model accuracies.

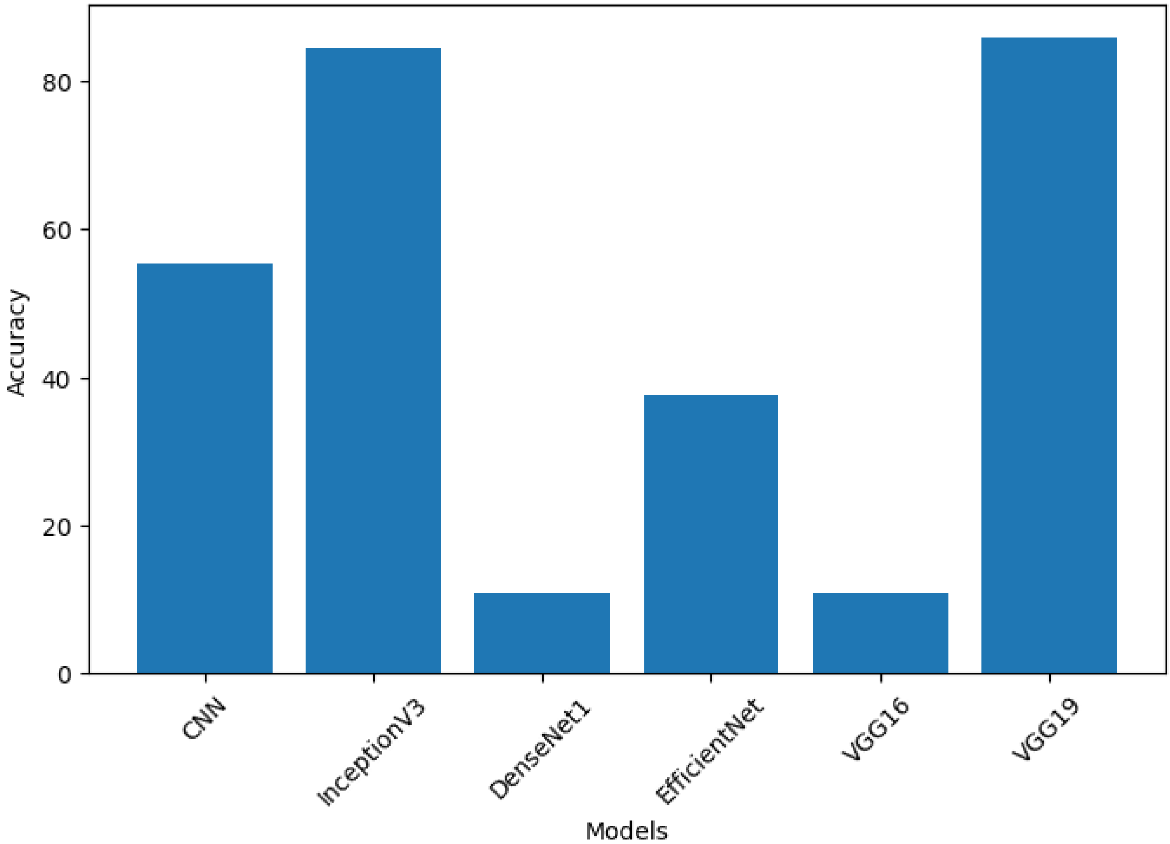



**Figure 15: Comparison of the model accuracies**

## 5.7 Discussion

Image pre-processing techniques like image rescaling and data augmentation were performed before training the model to improve the accuracy of the implemented models which exhibit different accuracy values for different models. The findings demonstrate a comparison of the performance of several CNN designs on the lung cancer classification task, as assessed by accuracy (see Table 1). With an accuracy rate of 84.47%, InceptionNet, and with an accuracy rate of 85.84%, VGG19 demonstrates that its architectures are more optimally configured to handle the unique characteristics of the provided dataset. The InceptionNet's high performance can be attributed to its intricate architecture, which incorporates different filter sizes within each convolutional block, enabling it to collect a diverse range of picture characteristics. The accuracy of normal CNN, Dense Net, models are varying between 37% and 55%. This observation suggests that although these models may be comparatively less advanced than InceptionNet, and VGG19, they are still capable of extracting significant characteristics that are relevant to the classification task. The highest performances of the models indicate that the performance may be limited by the capacity of the models' architecture or by the need of fine tuning the hyperparameters. Also, it shows that more training and optimization correspond more accurately to the data. Densenet1 and, VGG16, shows a significantly lower rate accuracy rate near to10 percentage. This indicates that these models are unsuitable for the given data set or application.

The use of computer tools to identify cancer cells in medical photographs is covered in the study. It lists challenges like requiring large amounts of labeled data and advanced computers. Doctors should find it simple to understand and stick to the programs' ethical principles. The study looks into alternative approaches to improving the programs and provides suggestions on how to improve a particular model.

# 6 Conclusion and Future Work

The main focus of this study was the use of deep learning approaches to classify lung cancer cells. This is a significant improvement in the domains of medical imaging and computational pathology. The main contribution of this research is the ability of CNN, to accurately differentiate between benign and malignant cancer cells in samples of cancer tissue. Most of the complicated patterns and characteristics in histopathological pictures are not easily recognizable by the naked eye. The results of this study show that the models trained are capable of recognizing these patterns.

CNNs were able to accurately differentiate between benign and malignant cancer cells due to their architectural design, which aims to match aspects of human visual perception. This enables CNNs to extract layered characteristics from unprocessed pixel input. CNNs enable a degree of analysis that aids pathologists in their diagnostic work and may even expedite it by autonomously acquiring the ability to recognize the intricate visual signals present in cellular structures. The study has provided more insight into the highlighted the importance of training data; both the quality and the amount of data, in developing more accurate models. The results show that a combination of CNN can handle complex problems such as cancer detection where different models have captured different features from data.
In future can work on the low performance of DenseNet1, VGG16 model, and exploring of ensemble methods to improve the accuracy.

# References

[1]. Deo, S.V.S., Sharma, J. and Kumar, S., 2022. GLOBOCAN 2020 report on global cancer burden: challenges and opportunities for surgical oncologists. Annals of surgical oncology, 29(11), pp.6497-6500.
[2]. Salomaa, E.R., Sällinen, S., Hiekkanen, H. and Liippo, K., 2005. Delays in the diagnosis and treatment of lung cancer. Chest, 128(4), pp.2282-2288.
[3]. Raquel, D. and Akhloufi, M.A., 2020. Deep learning for lung cancer nodules detection and classification in CT scans. Ai, 1(1), pp.28-67.
[4]. Shakeel, P.M., Burhanuddin, M.A. and Desa, M.I., 2022. Automatic lung cancer detection from CT image using improved deep neural network and ensemble classifier. Neural Computing and Applications, pp.1-14.
[5]. Asuntha, A. and Srinivasan, A., 2020. Deep learning for lung Cancer detection and classification. Multimedia Tools and Applications, 79, pp.7731-7762.
[6]. Ahad, M.A.R., Kobashi, S. and Tavares, J.M.R., 2018. Advancements of image processing and vision in healthcare. Journal of Healthcare Engineering, 2018.
[7]. Rahane, W., Dalvi, H., Magar, Y., Kalane, A. and Jondhale, S., 2018, March. Lung cancer detection using image processing and machine learning healthcare. In 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT) (pp. 1-5). IEEE.
[8]. Iqbal, M.S., Ahmad, W., Alizadehsani, R., Hussain, S. and Rehman, R., 2022, November. Breast Cancer Dataset, Classification and Detection Using Deep Learning. In Healthcare (Vol. 10, No. 12, p. 2395). MDPI.
[9]. Atwany, M.Z., Sahyoun, A.H. and Yaqub, M., 2022. Deep learning techniques for diabetic retinopathy classification: A survey. IEEE Access, 10, pp.28642-28655.
[10]. Haq, A.U., Li, J.P., Khan, I., Agbley, B.L.Y., Ahmad, S., Uddin, M.I., Zhou, W., Khan, S. and Alam, I., 2022. DEBCM: deep learning-based enhanced breast invasive ductal carcinoma classification model in IoMT healthcare systems. IEEE Journal of Biomedical and Health Informatics.
[11] M. A. Alzubaidi, M. Otoom and H. Jaradat, "Comprehensive and Comparative Global and Local Feature Extraction Framework for Lung Cancer Detection Using CT Scan Images," in IEEE Access, vol. 9, pp. 158140-158154, 2021, doi: 10.1109/ACCESS.2021.3129597.
[12] R. Singh, N. Sharma and R. Gupta, "Lung and Colon Cancer Classification using EfficientNet B3 Transfer Learning Model," 2023 World Conference on Communication & Computing (WCONF), RAIPUR, India, 2023, pp. 1-5, doi: 10.1109/WCONF58270.2023.10235069.
[13] M. Firdaus Abdullah, S. Noraini Sulaiman, M. Khusairi Osman, N. K. A. Karim, I. Lutfi Shuaib and M. Danial Irfan Alhamdu, "Classification of Lung Cancer Stages from CT Scan Images Using Image Processing and k-Nearest Neighbours," 2020 11th IEEE Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, 2020, pp. 68-72, doi: 10.1109/ICSGRC49013.2020.9232492.
[14]. Günaydin, Ö., Günay, M. and Şengel, Ö., 2019, April. Comparison of lung cancer detection algorithms. In 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT) (pp. 1-4). IEEE.
[15]. Wang, S., Yang, D.M., Rong, R., Zhan, X., Fujimoto, J., Liu, H., Minna, J., Wistuba, I.I., Xie, Y. and Xiao, G., 2019. Artificial intelligence in lung cancer pathology image analysis. Cancers, 11(11), p.1673.

[16]. Sajja, T., Devarapalli, R. and Kalluri, H., 2019. Lung Cancer Detection Based on CT Scan Images by Using Deep Transfer Learning. Traitement du Signal, 36(4), pp.339-344.
[17]. Bhatia, S., Sinha, Y. and Goel, L., 2019. Lung cancer detection: a deep learning approach. In Soft Computing for Problem Solving: SocProS 2017, Volume 2 (pp. 699- 705). Springer Singapore.
[18] J. Zhang and Z. Feng, "Inception DenseNet With Hybrid Activations For Image Classification," 2019 6th International Conference on Systems and Informatics (ICSAI), Shanghai, China, 2019, pp. 1295-1301, doi: 10.1109/ICSAI48974.2019.9010081.
[19]. Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556
[20] Q. Firdaus, R. Sigit, T. Harsono and A. Anwar, "Lung Cancer Detection Based On CT-Scan Images with Detection Features Using Gray Level Co-Occurrence Matrix (GLCM) and Support Vector Machine (SVM) Methods," 2020 International Electronics Symposium (IES), Surabaya, Indonesia, 2020, pp. 643-648, doi: 10.1109/IES50839.2020.9231663.
[21]. Tan, M. and Le, Q., 2019, May. Efficientnet: Rethinking model scaling for convolutional neural networks. In International conference on machine learning (pp. 6105-6114). PMLR.
[22]. Guo, Z., Xu, L., Si, Y. and Razmjooy, N., 2021. Novel computer-aided lung cancer detection based on convolutional neural network-based and feature-based classifiers using metaheuristics. International Journal of Imaging Systems and Technology, 31(4), pp.1954-1969.
[23]. S. R. Jena, T. George and N. Ponraj, "Texture Analysis Based Feature Extraction and Classification of Lung Cancer," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-5, doi: 10.1109/ICECCT.2019.8869369.
[24]. Ibrahim, D.M., Elshennawy, N.M. and Sarhan, A.M., 2021. Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases. Computers in biology and medicine, 132, p.104348.
[25]. Kanavati, F., Toyokawa, G., Momosaki, S., Rambeau, M., Kozuma, Y., Shoji, F., Yamazaki, K., Takeo, S., Iizuka, O. and Tsuneki, M., 2020. Weakly supervised learning for lung carcinoma classification using deep learning. Scientific reports, 10(1), p.9297.
[26]. Li, Z., Zhang, J., Tan, T., Teng, X., Sun, X., Zhao, H., Liu, L., Xiao, Y., Lee, B., Li, Y. and Zhang, Q., 2020. Deep learning methods for lung cancer segmentation in whole-slide histopathology images—the acdc@ lunghp challenge 2019. IEEE Journal of Biomedical and Health Informatics, 25(2), pp.429-440.
[27]. Liu, Z., Yao, C., Yu, H., and Wu, T., 2019. Deep reinforcement learning with its application for lung cancer detection in medical Internet of Things. Future Generation Computer Systems, 97, pp.1-9.
[28]. Hatuwal, B.K. and Thapa, H.C., 2020. Lung cancer detection using convolutional neural network on histopathological images. Int. J. Comput. Trends Technol, 68(10), pp.21-24.
[29]. Zhang, C., Sun, X., Dang, K., Li, K., Guo, X.W., Chang, J., Yu, Z.Q., Huang, F.Y., Wu, Y.S., Liang, Z. and Liu, Z.Y., 2019. Toward an expert level of lung cancer detection and classification using a deep convolutional neural network. The oncologist, 24(9), pp.1159-1165.
[30]. Radhika, P.R., Nair, R.A. and Veena, G., 2019, February. A comparative study of lung cancer detection using machine learning algorithms. In 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT) (pp. 1- 4). IEEE.
[31]. "The IQ-OTH/NCCD lung cancer dataset," www.kaggle.com. https://www.kaggle.com/datasets/hamdallak/the-iqothnccd-lung-cancer-dataset

[32]. LeCun, Y., Bottou, L., Bengio, Y. and Haffner, P., 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), pp.2278-2324.
[33]. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A., 2015. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1- 9).
[34]. Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q., 2017. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).
[35]. Thanoon, M.A.; Zulkifley, M.A.; Mohd Zainuri, M.A.A.; Abdani, S.R. A Review of Deep Learning Techniques for Lung Cancer Screening and Diagnosis Based on CT Images. *Diagnostics* 2023, *13*, 2617. https://doi.org/10.3390/diagnostics13162617
[36]. Neal Joshua, E.S., Bhattacharyya, D., Chakkravarthy, M., & Byun, Y. (2021). 3D CNN with Visual Insights for Early Detection of Lung Cancer Using Gradient-Weighted Class Activation. *Journal of Healthcare Engineering, 2021*.
[37]. Linde, G.; Chalakkal, R.; Zhou, L.; Huang, J.L.; O'Keeffe, B.; Shah, D.; Davidson, S.; Hong, S.C. Automatic Refractive Error Estimation Using Deep Learning-Based Analysis of RedReflexImages. *Diagnostics* 2023, *13*, 2810. https://doi.org/10.3390/diagnostics13172810.
[38]. Shadeed, Ghada & Tawfeeq, Mohammed & Mahmoud, Sawsan. (2020). Automatic Medical Images Segmentation Based on Deep Learning Networks. IOP Conference Series: Materials Science and Engineering. 870. 012117. 10.1088/1757-899X/870/1/012117.
[39]. Smith, A.D.; Du, S.; Kurien, A. Vision Transformers for Anomaly Detection and Localisation in Leather Surface Defect Classification Based on Low-Resolution Images and a Small Dataset. *Appl. Sci.* 2023, *13*, 8716. https://doi.org/10.3390/app13158716
[40]. Shaju, A., Shah, A., Iyer, G., Pandya, P., Sawant, V. (2023). Non-Invasive Anemia Detection Using Images Acquired from Smartphone Camera. In: Kumar, S., Hiranwal, S., Purohit, S.D., Prasad, M. (eds) Proceedings of International Conference on Communication and Computational Technologies . Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-19-3951-8_6.
[41] Chen, J., Zeng, H., Zhang, C., Shi, Z., Dekker, A., Wee, L. and Bermejo, I., 2022. Lung cancer diagnosis using deep attention-based multiple instance learning and radiomics. Medical physics, 49(5), pp.3134-3143.
[42] Civit-Masot, J., Bañuls-Beaterio, A., Domínguez-Morales, M., Rivas-Pérez, M., Muñoz-Saavedra, L. and Corral, J.M.R., 2022. Non-small cell lung cancer diagnosis aid with histopathological images using Explainable Deep Learning techniques. Computer Methods and Programs in Biomedicine, 226, p.107108.
[43] Talukder, M.A., Islam, M.M., Uddin, M.A., Akhter, A., Hasan, K.F. and Moni, M.A., 2022. Machine learning-based lung and colon cancer detection using deep feature extraction and ensemble learning. *Expert Systems with Applications*, *205*, p.117695.
[44] Shafi, I., Din, S., Khan, A., Díez, I.D.L.T., Casanova, R.D.J.P., Pifarre, K.T. and Ashraf, I., 2022. An effective method for lung cancer diagnosis from ct scan using deep learning-based support vector network. *Cancers*, *14*(21), p.5457.
[45] Shimazaki, A., Ueda, D., Choppin, A., Yamamoto, A., Honjo, T., Shimahara, Y. and Miki, Y., 2022. Deep learning-based algorithm for lung cancer detection on chest radiographs using the segmentation method. *Scientific Reports*, *12*(1), p.727.