A comparative study of CNN architectures for lung cancer detection from CT scan images

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Abstract

Diseases have been prominent cause of deaths. Early detection of diseases can exponentially decrease the death rates. Among many diseases, Lung cancer needs early stage identification to save life of human being. If it is not identified in the early stage then it causes the death of the human. The treatments during early stages have proven to be effective and saved the life of humans. Now the problem is to identify the lung cancer disease at early stage. Deep Learning plays a major to find the early stage of this disease from the given Computed Tomography (CT) images accurately. It is one of the popular and effective approaches in classification problems because it uses transfer learning and convolutional neural network. The accuracy for these kind problems can be increased by proper tuning the necessary parameters of model. This work focuses on implementation of pre-trained convolution neural network models which include Alexnet, VGG, ResNet-50, Densenet-121, Inception, and MobileNet with proper fine-tuning of the necessary parameters. In this work, the benchmark dataset "IQOTHNCCE lung cancer CT scans images" is considered to check the performance of these pre-trained models. Each of the implemented models is evaluated on the basis of performance metrics such as Balanced Accuracy Score, Precision, Recall, and F1 score. The Inception model performed best with balanced accuracy score of 99.8% among other models.

Keywords: CT Lung cancer detection, CNN, Deep Learning, Transfer Learning

1. Introduction

Lung cancer is one of the most common types of cancer, accounting for a high number of deaths each year, and this number has been rising in recent years as a result of high levels of smoking and air pollution [23, 2]. According to the data given by the "World Health Organization" (WHO), lung cancer contributes to approximately 7.6 million worldwide deaths. It is estimated that by 2030, the death rate would reach up to 17 million due to same cause. Based on the records from the Global Cancer Observatory, owned by the World Health Organization/International Agency for Research on Cancer, Lung cancer stood the 2nd most among other types of cancers. It is considered to be 2nd common cancer in females and top among males. More than 2.2 million new cases of lung cancer were diagnosed in 2020, according to a review by abdullah el. al. [1]. The primary reasons include smoking, unhealthy food and water, and uncontrolled air pollution. To overcome the number of deaths due to this lethal disease, huge amount of research has been already done in past and also being done in the present. Several studies and research have worked on various techniques for early detection Artificial Intelligence has been contributing immensely in almost every field now. Machine Learning (ML) and Deep Learning (DL) are two subsets of artificial intelligence. Several Machine Learning algorithms [26,27] have been already implemented to solve many problems such as classification problem, cluster problem, etc. Some of the popular machines learning algorithms for classification problems are Support Vector Machine, K-Nearest Neighbor, etc. Due to automatic feature extractions from images, Deep Learning algorithms are used to solve problems in variant of domains such as computer vision, speech processing, etc. Deep Learning algorithms are best suited as the results obtained from them have higher accuracy due to its complexity than classical ML algorithms [9]. Recently, many researchers achieved high accuracy on classification problems by employing deep learning algorithms. Hence, the early detection of lung cancer using deep learning algorithm are discussed in the present work. Since the last decade, two types of datasets have been used for the detection of lung cancer, one based on Computed Tomography (CT) scan images and the other on X-Rays. CT scans have provided better accuracy and hence are most widely used for predictions [9]. Convolution Neural Networks (CNN) have been popular and are well suited for image classification as it provides better accuracy in a short time with minimized pre-processing [12]. This gives the ultimate scope to detect lung cancer for a given set of CT scan images of the lung. Two different ways of using CNN in disease detection in the medical field [7]. The naive approach where the model is built from scratch with all layers and parameters set according to the problem statement. But this approach needs more time for training model building and also requires a huge dataset for better performance in the training phase. Transfer Learning (TL) based is another approach. In this approach, the reusability of the pre-trained model with changes at the last few layers is taking place with respect to the problem statement. This saves computational costs and resources. The various pre- trained models include Alexnet [2], VGG [14], ResNet [15], Inception [24-20], DenseNet, MobileNet. This work focuses on the detection of lung cancer at an early using a pre-trained model for a given set of CT images as input. These models are evaluated with performance metrics and also made the comparison study on lung cancer detection problem. Many researchers have been done detection of Lung cancer from CT scans using different pre-trained models. Hence, this work focuses on comparisons of various pre-trained models which have a significant difference in the architecture of the model. In the existing literature, the dataset is not much explored by many researchers. One of the observations is, the selected models have performed significantly better in different domains, and hence the researcher adopted the same pre-trained model.

Rest of the paper is organized as follows. Section 2 presents the work related to CT lung cancer detection, with particular emphasis on CNN approaches for lung cancer detection. Section 3 briefs about CNN architectures used in the present study and the dataset. Sections 4 describe the experiments and report the lung cancer classification using different CNN architectures. Finally conclusion and future work are given in Section 5.

2. Related work

The detailed survey on various machine learning techniques to detect the lung cancer is presented in [1]. These machine learning algorithms are applied on both types of dataset images including CT scans as well as X-ray images. In past works, different classifiers have been used like Naive Bayes, Gradient Boosted Tree, K-nearest neighbors, Neural Networks, and Decision Tree for this lung cancer detection problem. But it has been evident that approaches under Deep Learning have performed well in most of the cases, because, the researchers need to concentrate on best algorithms to extract the features from images.

A great deal of research happened on the prediction of lung cancer using CT scans and X-Rays images of lungs. Hamdalla F. Al-Yasriy et al. [2] implemented the Alexnet architecture using the dataset "IQ-OTH/NCCD". The accuracy was reported as 93.5%. Dandil et al. [7] developed a Computer Aided Design (CAD) system for ensuring the early detection of lung cancer and successfully classified benign and malignant tumors. But the author used a small dataset consists of 128 CT images which are collected from 47 patients. Tasnim et al. [16] used 3D CNN to detect cancer in lungs using the LUNA-16 dataset. They have done pre-processing using manual thresholding and segmentation. Bijya et al. [9] built a convolution neural network with five layers to classify the histopathology colored images into 3 classes- benign tissue, Adenocarcinoma, and squamous carcinoma cells. The numbers of hidden layers were three, with one input and one fully connected layer. The accuracy reported was 96.11%. Anubha et al. [8] after pre-processing trained the dataset on two models- Alexnet and Manual CNN written from scratch. In this case Manual CNN performed better with 90.5% accuracy. Sarah et al. [4] implemented five Convolution Neural Network architectures (CNN) and compared them on the performance metrics – accuracy, sensitivity, specificity and AUC. They classified LIDC- IDRI dataset into two categories- Benign and Malignant.

E. Cengil et al. [5] used deep learning methods to detect lung cancer using Tensor Flow libraries and 3D-CNN architectures in the proposed system. It worked on a SPIE-AAPM-LungX dataset of CT images. The recorded accuracy of the model is 70%. In Yu Lu et al. [14] proposed approach to detect lung nodule using VGG-16 and dilated convolution network. Later the proposed model was compared with the tradition segmentation techniques such as Hausdroff distance and Jaccard similarity coefficient. VGG outperforms the traditional approaches with accuracy of 97.1%. In [19], several pre-trained models are hyper-tuned by considering several factors. Histopathological images were used to categorize them into three categories. ResNet 101 had the best accuracy among all of these CNN models, at 98.67% accuracy. Diego et al. [17] suggested the hybrid model with deep leaning and traditional machine learning approach combined together. The author is divided the work into two stages – Lung Nodule detection system and false positive (FP) reduction system. The authors are also tried to explore all the available dataset related to lung cancer. Densely connected network along with the U-net architecture performed very well in this case. Z.Shi et al. [20] proposed a deep Convolutional Neural Network (DCNN). The system used transfer learning for finding a pulmonary nodule on CT scans. Pre-trained CNN architecture was used for feature extraction. The model selected was VGG16 and the classifier was Support Vector Machines (SVM).

Aparna el at. [15], proposed the model that implemented pre-trained model - Residual Network (ResNet) for feature extraction. These features were used to train the model built using Support Vector Machine classifier. R.V.M.D. et al. [6] implemented various pre- trained models to extract features to process LIDC-IDRC image dataset. These features were later utilized to classify using different classifiers such as Naive Bayes, Decision Tree, SVM, and KNN. Performance of the classifiers was compared based on metrics such as Area under curve, Precision, and True Positive Rate. ResNet performance was better than others with accuracy of 88.41%. Cheng et al. [24] used Inception V3 model for classification pulmonary images. In this research work, the Inception V3 model was compared with the Deep Convolution Neural Network (DCNN). The Inception V3 model performed better with sensitivity of 95.41 %. The normalization of data was done using z-score standardization method.

3. Proposed Methodology

3.1. Convolutional Neural Network Architecture

Convolution Neural Networks are the part of Artificial Neural Network, mainly dealing with the analysis of visual related problems in the real world. There are several image classification algorithms present but CNNs are the most effective, due to its minimized pre-processing steps and automated lean- ing concepts through feature extraction makes it best for image classification domain problems. The introduction of transfer learning concept has eased the classification process to more simplified version, making it look more easy and fast. Transfer learning is the technique of re-using existing models to solve the new problems of any domain. The previously learnt knowledge is utilized to perform new task on the given new problems. Transfer learning has eased the processed to easy level with reduced time complexity. It does not train the model from scratch and hence saves a lot of time from days to hours and lot of computational resources too. To speed up the development of new models, any transferable knowledge or features can be decided to move between networks. The transfer of knowledge across different tasks or environments is a critical component of constructing such a network. Transfer learning is typically confined to general tasks that are applicable in a variety of scenarios. Lack of training data is a widespread problem when using deep CNN model, which involve a large amount of data to complete task. Collection of a large dataset is time-consuming, and sometimes not an easy option. As a result, the transfer learning approach is useful in addressing the issue of limited data collection. Transfer learning is a method in which CNN models are trained on huge datasets and then fine-tuned to train on a small required dataset for a specific domain.

Transfer Learning uses pre-defined existing models (like Alexnet [13], InceptionNet [22], Mobilenet [18]) by implementing few problem specific improvements in the architecture of these models. These models have already been trained on huge dataset of “imagenet” with 1000 classes in the classification task. In this work, these existing models have been implemented with required changes in the last few layers concerned with classification of CT scan images into 3 categories like Normal, Benign and Malignant. These adjustments in the last and fully connected layers are done in order to fit the model according to our problem and dataset. Fig.1 shows the generalized architecture of pre-trained models used in the work.

There has been implementation of six models for classification of CT scan images into three categories. Fig. 2 shows the basic structure of proposed system, where each model is fed with same dataset and evaluated. Each Model has different number of layers (depth) and trainable parameters as shown in Table-1, Hyperparameters followed by models are shown in Table-2. Each model has been modified according to the problem requirement. The six models considered in the present study are described below.

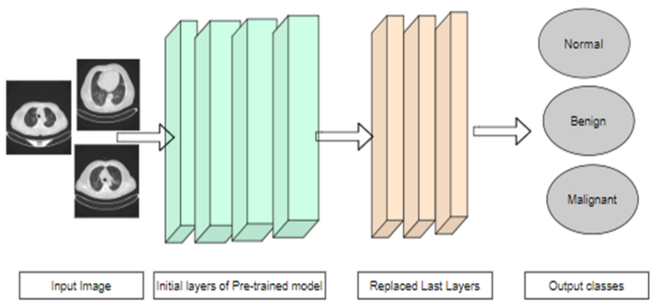

Fig. 1. Generalized architecture for proposed methodology

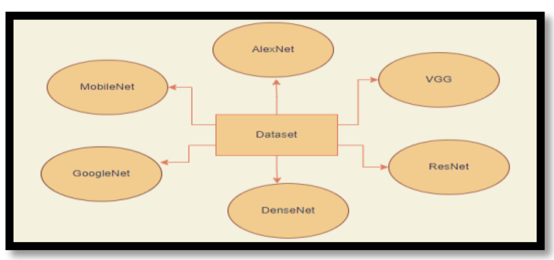

Fig 2. Proposed Architecture with six pre-trained models

AlexNet [13]: This pre-trained model used five convolution layers, the last three layers comprises of two dense layers or the fully connected layer and a softmax or the output layer to classify the image into relevant class out of the three classes. Kernel size has been varied from 11x11 to 3x3 till fifth convolution layer. Input size of image is 224x224. Dropout of 0.4 makes sure that over fitting is avoided.

VGG [21]: The last four layers include three fully connected layers with one output layer classifying input into relevant classes. These four layers are connected to the transferred layers (pool5). Drop out in between dense layers is used to avoid over-fitting.

ResNet [10]: The network layers (fc1000 and Classification Layer) are replaced with fully connected layer (fc56), and classification output layer. Afterward, the last remaining transferred layer on the network (pool5) is connected to replaced layers.

DenseNet121 [11]: The output of transferred layers is passed through GlobalAveragePooling2D, Batch_Normalization and Dropout layers. The last added layers are two fully connected layers and one softmax output layer. These layers are added to the transferred layers, global_average_pooling2d_1 of pool5.

Inception [22]: The last two layers of the network are modified. The layers loss3-classifier and classification output layer are adjusted with a fully connected layer and an output layer. Later, the last transferred layer still existing on the network (mixed_10) is connected to the new layers.

MobileNet [18]: Similarly, the last three layers of the network are changed. The data required to combine the features that the network collects into class labels and probabilities is contained in these layers. The layers loss3-classifier and classification output layer are replaced with two fully connected layers and an output layer. The last transferred layer of the network (block_16_depthwise) is connected to the new layers after flattening the input.

Table 1 Properties of pre-trained networks

Network	Depth	Parameter (Millions)	Input Size
Alexnet	18	32	224 x 224
VGG	16	14	224 x 224
ResNet	50	35	224 x 224
Inception	48	156	224 x 224
DenseNet	121	8	224 x 224
MobileNet	53	4	224 x 224

Table 2 Hyper parameters and their values

Hyper-Parameters	Value
Optimization Technique	Adam
Learning Rate	0.001
Epochs	10
Batch Size	33
Activation Function	ReLu and Softmax
Drop out	0.4

4. Results and Discussion

4.1. Dataset Description

The Iraq-Oncology Teaching Hospital/National Center for Cancer Dis- eases (IQ-OTH/NCCD) lung cancer dataset [3] is used for this problem. It was collected in the Iraqi specialist hospital for over a time period of three months in 2019. It includes CT scans of patients skeptical of lung cancer at various stage and normal cases as well. There are total of 1190 images representing the CT scans of lungs comprising of 110 patient cases. These cases include patients from various occupation, residence area, living status, age, and gender with the purpose of collecting data with enough variations.

Normal, benign and Malignant are considered as three classification categories. Each CT scan images contains several slices ranging from 80-200 slices with different angles and sides. The slice thickness is of 1 mm, with window width ranging from 350 to 1200 HU and window center from 50 to 600. The dataset is easily accessible on Kaggle. The few samples from the dataset are given in Fig. 3.

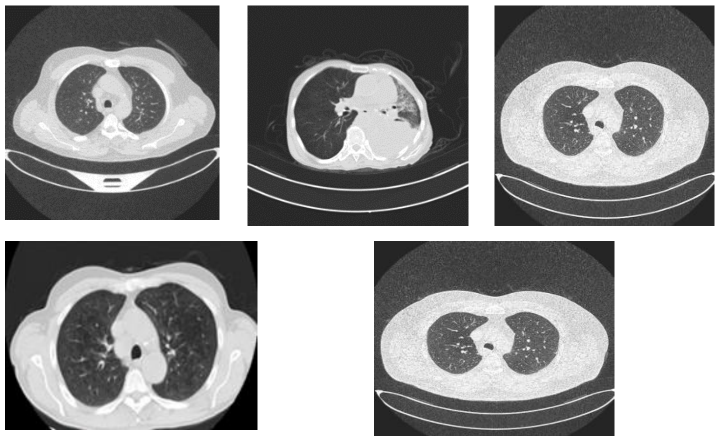

Fig. 3. Sample of CT scan images

4.2. Evaluation Metric

The six implemented model have been evaluated using various performance metrics such as confusion matrix, balance accuracy score, F1 score, precision, recall and loss. The balanced accuracy score is useful in multiclass classification problems to handle the imbalanced dataset. It is simply the average of recall of all the classes. F1 score being the harmonic mean of precision and recall is rated best at 1 and worst at 0. The parameters and equations are as follows. True Positive (TP) Cases having both actual and predicted value as yes. True Negative (TN) – Cases having both actual and predicted value as no. False Positive (FP) – Cases having actual value as no but predicted value is yes. False Negative (FN) - Cases having actual value as yes but predicted value is no. The equations for Accuracy, Precision, Recall and F1 score are given Equation- 1, 2, 3 and 4 respectively.

In this research, The IQ-OTHNCCD lung cancer dataset has been used; the dataset is obtained from Iraqi hospital. It Includes 1100 CT images divided into three categories i.e. the normal cases with no lung cancer and other two categories being the benign and Malignant lung cancer. Deep learning algorithms require huge amount of data to efficiently work on the training dataset. In these cases, Data augmentation technique is used to increase the number of labeled data. Transfer learning reduces the huge requirement of training data and also reduces the training time for algorithm.

Table 3 Comparative Result analysis of six pre-trained models

Model	Accuracy	Precision	Recall	F1_Score
Alexnet	0.909	0.921	0.909	0.905
VGG	0.890	0.908	0.890	0.877
Resnet	0.873	0.788	0.873	0.826
Densenet	0.964	0.976	0.964	0.966
Inception	0.998	0.998	0.998	0.998
Mobilenet	0.918	0.914	0.904	0.918

In the problem, the dataset has been divided into 3 categories of Lung state; the training and testing split accounts for 90 - 10% respectively. Six pre- trained models (AlexNet, VGG, ResNet, DenseNet, Inception, Mobilenet) were trained using concept of fine-tuning. In each model, the last layers have been modified and last layer which used softmax as activation function was well matched with the number of required classes i.e. 3 classes in this case. These models were evaluated using performance metrics such as balanced accuracy, precision score, recall score, F1 score as shown in Table 3. The table shows general comparison of the performance of all the six models.

The comparative analysis of all the pre-trained models on the "The IQ- OTHNCCD lung cancer" dataset for classification in three categories using CT scans was completed. The main purpose was to have an overview of pre-trained model and making predictions after comparing them.

The models overall performed well having significant accuracy and scores. The accuracy of Inception model is 99.8% while the accuracy of Resnet (87.3%) is the lowest among the six models being compared. The precision, recall and F1 score are again highest for Inception. Inception model is the best among all as it has 99.8% accuracy for training and testing both dataset.

The accuracy of VGG is recorded to be 89%, Resnet to be 87.3%, Densenet is 96.4%. These accuracies were well supported by the precision and re- call scores. Fig 4 to Fig 13 shown the training and validation accuracy and losses for each model along with confusion matrix for AlexNet, VGG, ResNet, DenseNet, Inception, Mobilenet. The graphs show the accuracy and loss of every epoch ranging from 1 to 10 for all the six models. The rows are present with the predicted class, while the columns are present to the actual class.

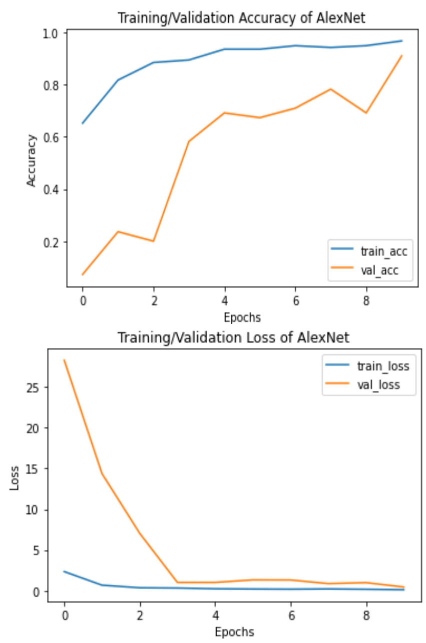

Fig.4. Training / validation accuracy and loss of Alexnet

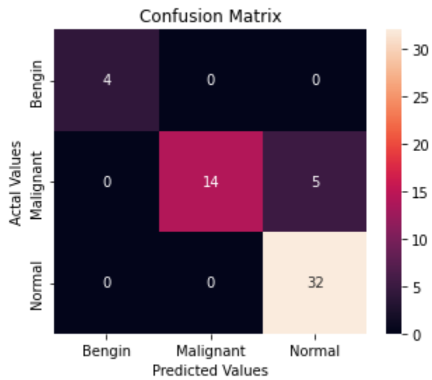

Fig. 5. Confusion matrix of AlexNet using heat map

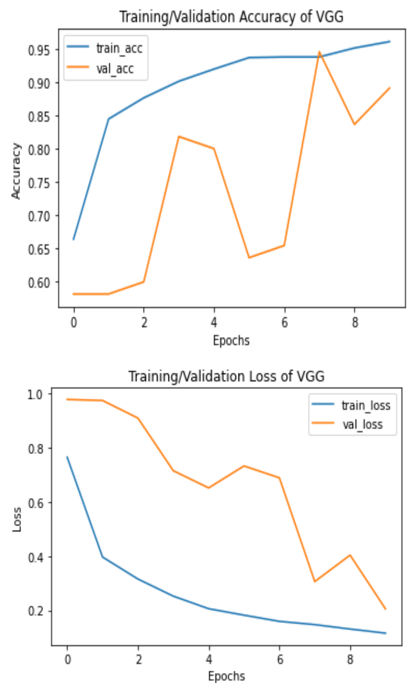

Fig.6. Training / validation accuracy and loss of VGG.

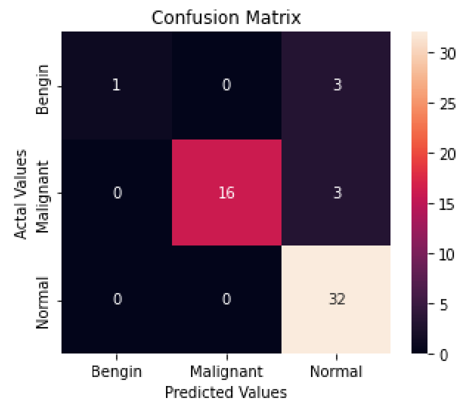

Fig. 7. Confusion matrix of VGG using heat map

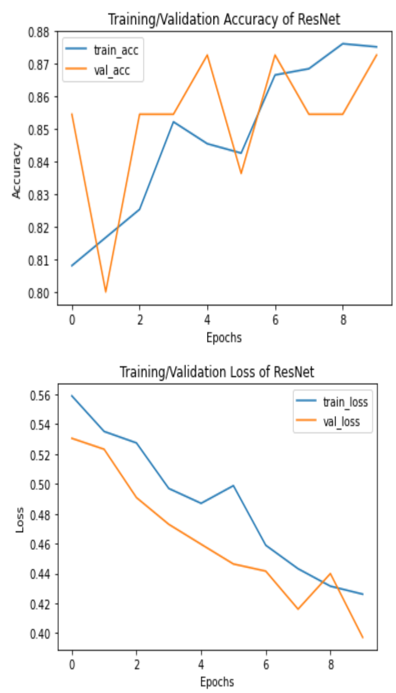

Fig. 8. Training/validation accuracy and loss of ResNet.

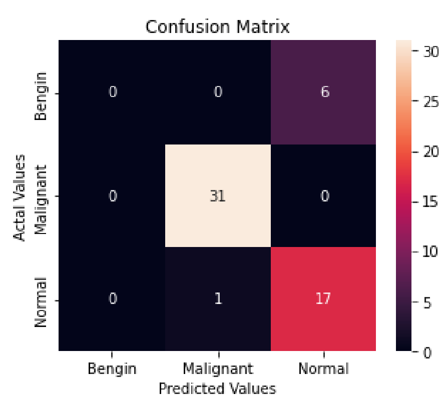

Fig. 9. Confusion matrix of ResNet using heat map.

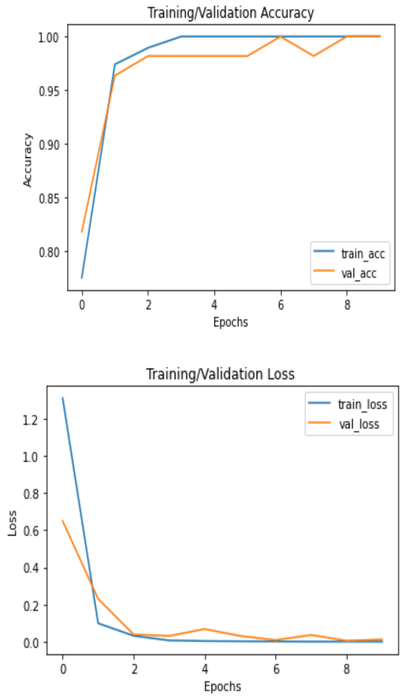

Fig 10 Training / validation accuracy and loss of Inception

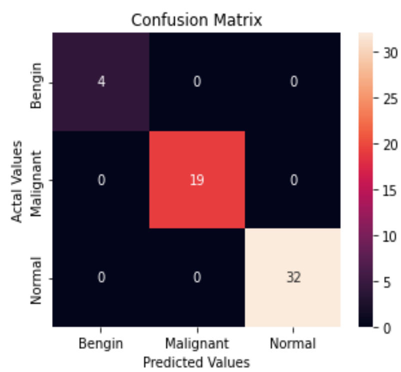

Fig.11. Confusion matrix of Inception using heat map.

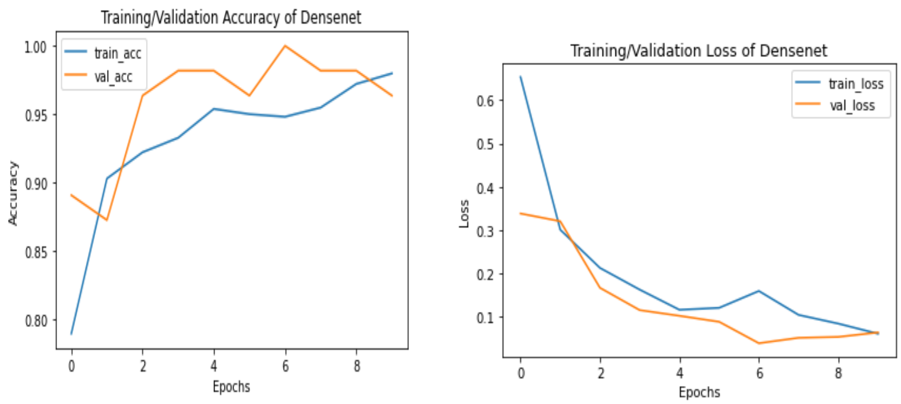

Fig 12 Training / validation accuracy and loss of Densnet

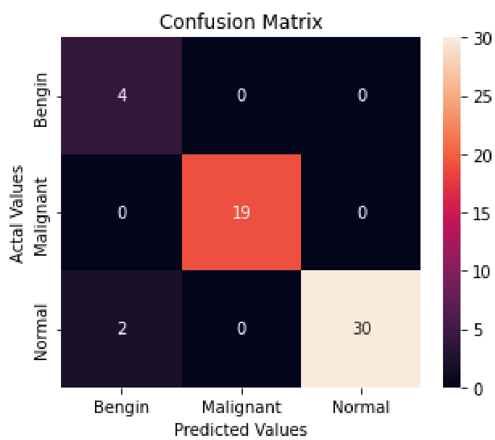

Fig13 Confusion matrix of DenseNet using heat map

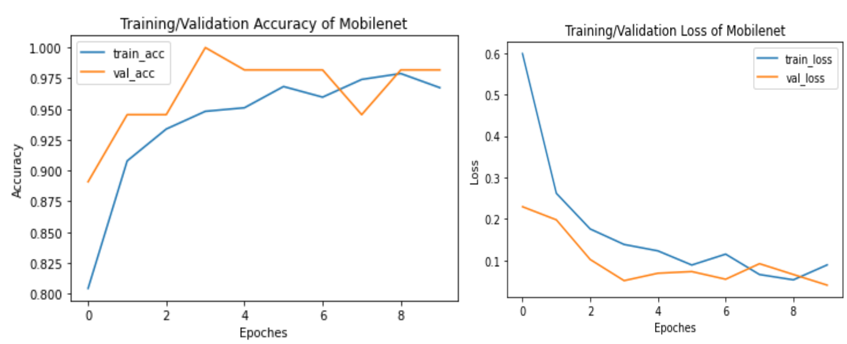

Fig 14 Training / validation accuracy and loss of Mobilenet

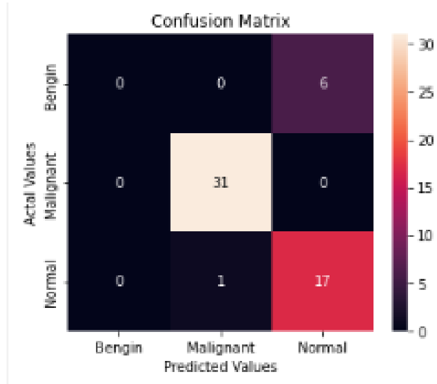

Fig 15 Confusion matrix of MobileNet using heat map

4.3. Computational Analysis

These models have been trained using GPU to significantly speed the machine learning operations. The Alexnet model required the least training time of 42.84 seconds while Mobilenet Model took 720.09 seconds for complete training the dataset for 10 epochs. The Table 4 below shows the training time, RAM used and the Space used by the disk for each of the trained model.

Table 4. Computational analysis of models.

Model	Run Time (sec)	RAM (GB)	Disk (GB)
ALEXNET	42.84	5.04	39.44
VGG-16	83.53	4.62	39.69
RESNET-50	52.83	1.30	38.91
INCEPTION	87.90	4.12	39.16
DENSENET	69.26	4.86	39.15
MOBILENET	720.09	3.07	38.80

4.4. Result Analysis

This study is done on small dataset of 1100 CT scan images. These six models have performed significantly well. One of the oldest models, Alexnet took least training time of 42 seconds and accuracy of 90%. Inception is a model with deeper network through a dimensionality reduction with stacked 1x1convolutions. It performed best with accuracy of 99% and overall training time of 87 seconds. Densenet which has all the layers interconnected as Dense Blocks has performed well with accuracy of 96%. The least recorded accuracy 87.3% which is produced by Resnet-50.

5. Conclusion

Deep learning is an effective approach in the classification problems. But it requires a huge amount of data. To solve this issue of huge dataset, Transfer learning comes into play. It tackles the issue of huge dataset and re-using the existing built model. With the help of fine-tuning, these models can be utilized specifically for our own problem statement. This work focuses on comparative analysis of six pre-trained model based on various performance metrics. Each model has obtained significant accuracy in epoch of 10. By using these models, we can classify the given CT scan image into three categories- normal, benign and malignant. This early detection will help the patients and decrease the death rates. In future, the work can be extended by implementing various other pre-trained models and also using other lung cancer dataset.

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