Lung Cancer Prediction using CT medical imaging

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ABSTRACT

Cancer at an early stage is curable with a high success rate. As lung cancer is among the top three cancers worldwide, its early-stage detection and prediction play the most crucial role in cancer prevention. However, the most challenging task for medical professionals is to diagnose cancer in its early stages. Advanced AI-based assisting systems help in detecting lung cancer accurately and effectively assist doctors. However, for any AI-based system to predict cancer accurately, it should get access to a reasonable amount of patients' digital data. While low-dose computed tomography (LDCT) and computed tomography (CT) scans provide a greater insight comparing x-ray images, accessing this digital data can be challenging. This paper proposed an efficient model that accurately predicts whether a patient is suffering from lung disease or not, based on a CT scan image. The paper's main objective is to train an AI model that can assist medical professionals in detecting lung cancer from CT images without having access to a large dataset of biomedical images to train the model. The authors have implemented a specific type of image augmentation and pre-processing on a relatively small CT image dataset and have trained hybrid Convolutional Neural Network (CNN) models for better performance.

KEYWORDS

Deep learning, Cancer detection, CT images, Ensemble models

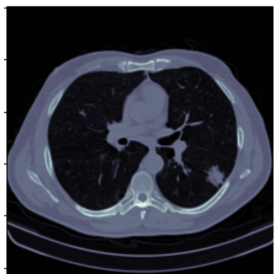
1 INTRODUCTION

One of the leading causes of death worldwide is cancer; one out of six people died due to cancer in 2020. Out of 10 million deaths caused in 2020 due to cancer, approximately 22% of people died due to lung cancer [24]. As per medical professionals, in most cases, the main reason for deaths due to lung cancer is because its symptoms came into notice at the final stage of cancer. As a result, doctors and researchers across the globe found lung cancer detection in the early stages the most tedious and stimulating task. This is the reason for the high death percentage in lung cancer compared to all other types of cancers [16]. Numerous factors cause lung cancer like smoking, exposure to secondhand smoke or radon gas, and previous radiation therapy are the most common risk factors that cause lung cancer [5]. In [5], the authors have mentioned some symptoms that are commonly seen in lung cancer patients when the disease is in its advanced stage. The symptoms include a regular cough that might sometimes come up with blood, shortness of breath, chest pain, bone pain, weight loss without effort, and constant headaches [5]. However, it is hard to detect lung cancer in the early stage without these kinds of alarming symptoms. Medical practitioners categorized lung cancer into four categories below [23]:

- Stage 1: This stage's cancer is considered small cancer and easily curable as it has cancer of up to 4 cm. This stage is divided into two subcategories.
  - Stage 1A: The cancer is less than 3 cm or equal to 3 cm in size.
  - Stage 1B: The cancer is between the size of 3 cm to 4 cm.
- Stage 2: Up to this category, cancer can be called early-stage cancer. Stage 2 is known as Non-Small Cell Lung Cancer (NSCLC). This stage also has two subcategories.
  - Stage 2A: The cancer is between 4 cm to 5 cm, and no cancer cell is present in the lymph nodes.
  - Stage 2B: The cancer is up to 5 cm in size with cancer cells in lymph nodes close to cancer affected lung.
- Stage 3: Cancer of this stage is advanced cancer and is divided into three subcategories.
  - Stage 3A
    - Cancer is up to 5 cm and has affected lymph nodes on the same side of the tumor.
    - Cancer is between 5 cm and 7 cm, and more than one tumor is on the same side of the lung.
    - Cancer has affected one or more body parts such as the chest wall, nerve near to lungs, lymph nodes in the lung, and the layer that covers the heart.
    - Cancer is more than 7 cm in size and does not spread in lymph nodes but is present in any muscle near the lungs, chest area, heart, blood vessel, spinal bone, etc.
  - Stage 3B:
    - Cancer is less than 5 cm and present in the neck, above the collarbone, or opposite of affected lung of lymph nodes.
    - Cancer is between 5cm to 7cm and presents in lymph nodes in the center of the chest.
    - Cancer of any size that is present in either the chest wall, muscle near the lung, or layer covering the heart.
  - Stage 3C:
    - Tumors in more than one lube of lungs or more than one tumor in a different lobe of the same lung.
    - Cancer is between size 5 cm and 7 cm and has affected one or more nerves near the lungs and has spread into lymph nodes in any way.

    * Cancer of more than 7 cm in size has spread in lymph nodes and affected any of the nearest areas.
- Stage 4: This is the last stage of lung cancer that can be in two subcategories.
  - Stage 4A: Cancer has affected both lungs or has fluid in the lung or heart that contains cancer cells.
  - Stage 4B: Cancer has spread and affected more than one organ.

(a) Category 1



(b) Category 2

Figure 1: DICOM image from cancer dataset

Figure 1 shows the DICOM (Digital Imaging and Communications in Medicine) images of the CT scans. Figure 1 has two images in it which are taken randomly from both binary categories. As seen in the Figure 1 both of the images seem equal and it's hard to distinguish from the naked eye to categorize.

Detecting lung cancer in an early stage is becoming possible due to advances in AI's subdomains such as computer vision and deep learning. Detection of lung cancer using medical imaging is one of the most interesting areas for researchers across the globe. The researchers are highly influenced by the advancement of computer vision and deep learning technologies in the healthcare industry for the betterment of human society. As a result of advancement, AI-based advanced models can accurately understand complex characteristics of lung cancer from medical data. CNN-based state-of-the-art models have shown promising results to detect and segment diseases from medical imaging and are dominating the healthcare field [13]. Advanced CNN-based models have proven to be very efficient and effective with images in the computer vision domain for recognition and classification tasks. The researchers have made significant improvements in the CNN models from time to time [1]. Starting with first LeNet-5[12] proposed in 1998, AlexNet[11] in 2012, VGG-16[17] in 2014, Inception[20] in 2015, InceptionV3[21] in 2016, ResNet-50[8] in 2016, Xception[4] in 2017, InceptionV4[18] in 2017, Inception-ResNets[19] in 2017, ResNeXt-50[25] in 2017, DenseNet[10] in 2017, MobileNet[9] in 2017, NASNet[27] in 2018 and EfficientNet[22] in 2019. These are some of the best-performing CNN models on the ImageNet dataset [6]. The models are trained and tested on the ImageNet dataset and can be used as a transfer learning model with trained parameters on this dataset.

1.1 Motivation behind Problem statement

At present, medical professionals use diagnostic tests to identify lung cancer in its early stages. However, it is not an easy task and straightforward task, hence there is a scope for misdiagnosis of lung cancer in its early stages. To assist medical professionals in accurately predicting lung cancer at its early stages, the authors of [2] used a multi-class SVM Classifier for multi-stage lung cancer detection and prediction on CT images. In this way, Machine Learning(ML) has proven to overcome the diagnostic test issue of misclassification. The Deep Learning(DL) technique is observed to work more efficiently compared to ML techniques for image classification tasks. In this paper, the authors are proposing hybrid CNN-based models to classify CT scan images into binary classes having lung cancer or not. The proposed model is evaluated using numerous performance metrics such as precision, recall, and accuracy.

2 RELATED WORK

This section represents the researcher's state-of-the-art models in recent years for lung cancer detection. The authors of the paper [15] have divided images of lungs based on morphological smoothing and region growing technique and then used k-nearest-neighbor for the classification task. The authors got promising results with their novel approach for detecting lung cancer with an accuracy of 84%. In the paper[26], Ye et al. segment the lung region from the CT image using a fuzzy thresholding method and apply pre-processing to the segmented lung portion. Then weighted support vector machine classifier was used to reduce the number of false positives (FP) in the test set. Messay et al. [14] proposed a computer-aided detection(CAD) system including pre-processing steps as morphological handling and thresholding with two distinct classification models; the Fisher Linear Discriminant Classifier and Quadratic Classifier, which achieved an accuracy of 82.66%. Gomathi et al. have pre-processed data with boundary extraction, region growing, and gray-level histogram thresholding. Then, the authors have segment images portion that has an abnormality. The authors have implemented several models such as rule-based methods, minimum distance classifiers, cascade classifiers, Bayesian classifiers, Multilayer perception, Radial Basis Function network (RBF), Support Vector Machine (SVM), Artificial Neural Networks, and Fuzzy logic. Alam et al. have proposed a multi-class SVM classifier to detect and predict multi-stage lung cancer in [2]. The author classifies lung cancer in step by step process, first they binary classify whether the cancer is in the first stage or not. If the cancer is classified as in the first stage, then the authors in the second part try to detect the stage of cancer or else try to predict the probability of cancer to be of the second stage. In the paper[16], the author presents a comprehensive approach towards lung cancer detection using machine learning techniques. Further, the authors provide a rich literature review about applications of machine learning in lung cancer detection. The authors also discuss different algorithms that are effectively applied as CNN models, Fully Convolutional

Networks (FCN), and Auto-Encoders(AE). The paper also provides a table containing highlighted work in a cancer detection task with promising results. The authors of paper[3] have implemented deep learning-based advanced CAD to classify chest x-ray images for lung cancer with an accuracy of 74%. The authors have used 121 layers dense convolutional neural network, commonly known as DenseNet-121, with extensive pre-processing steps. The authors have also used a small dataset with DenseNet-121 and found promising results on x-ray images for lung cancer detection.

3 METHODS

This section describes the architecture of the proposed model. Staring at, the dataset description that was used in the proposed model. As the dataset has a few samples of each category, it is necessary to pre-process the dataset for augmentation and better performance of the model. This section also covers the motivation behind the proposed model. Then, the performance of the proposed model is also evaluated on the holdout dataset.

3.1 Dataset Description

The dataset of CT scans of the chest is referred from the Kaggle dataset [7] in the png/jpg format. The dataset is consist of a total of 1000 images of size 224×224 resolution with four different categories in it. Out of these four categories, three categories are of three different types of lung cancer and the last one is of normal CT images. Dataset categories and their descriptions are as follows:

- *Adenocarcinoma:* Lung adenocarcinoma is the most common form of lung cancer accounting for 30 percent of all cases overall and about 40 percent of all non-small cell lung cancer occurrences.
- *Large-cell carcinoma:* Large-cell undifferentiated carcinoma lung cancer grows and spreads quickly and can be found anywhere in the lung.
- *Squamous cell carcinoma:* This type of lung cancer is found centrally in the lung, where the larger bronchi join the trachea to the lung, or in one of the main airway branches.
- *Normal:* The CT images do not have any evidence of lung cancers.

The data was already split by the author as shown in Table 1.

Table 1: Dataset Split category-wise

Category	Training	Validation	Testing	
Adenocarcinoma	195	23	120	**338**
Large Cell	115	21	51	**187**
Squamous Cell	155	15	90	**260**
Normal	148	13	54	**215**
	613	**72**	**315**	**1000**

3.2 Pre-Processing

As the CT scan images data are only 1000 images, there's a scope for necessary data preprocessing as well as data augmentation. To augment the data, the authors have used the ImageDataGenerator module that augments the train and test data with hyper-parameter values rotation_range = 15, shear_range = 0.2, zoom_range = 0.2, horizontal_flip = True, fill_mode = 'nearest', width_shift_range = 0.1, and height_shift_range = 0.1. The authors have also re-scaled the image pixels data of train, testing, and validation by dividing the values by 255. The authors have used batch_size as 8 to train the model.

3.3 Model Motivation

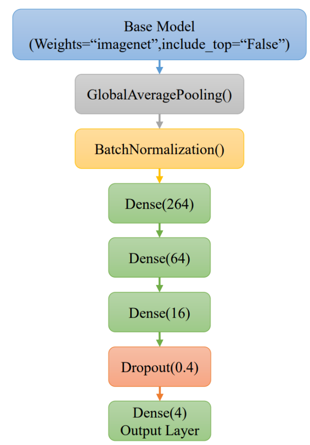


Figure 2: Architecture of the models

As per the explored literature in the previous section, the authors have found that complex CNN models have shown promising results for lung cancer classification. The authors have explored models such as DenseNet, MobileNet, ResNet, EfficientNet, VGG, Inception, and Xception and analyzed the performance of these models on the given small amount of dataset. The authors have understood the domain's requirements as the classification model should have high recall and accuracy. The authors have trained the listed models in Table 2 having architecture shown in Figure 2.

Table 2: Models' performance on the testing(holdout) data

Model	Loss	Accuracy	Recall	Precision
DenseNet169	**0.547894**	**0.853968**	0.93968	0.45963
DenseNet201	0.759781	0.765079	0.87619	0.57381
EfficientNetB4	0.995534	0.55873	0.82857	0.4579
InceptionV3	0.624704	0.793651	**0.94286**	0.44461
MobileNet	0.559497	0.825397	0.93651	**0.65121**
ResNet50	1.123878	0.514286	0.6	0.32643
VGG19	0.706449	0.72381	0.77778	0.58612
Xception	0.828387	0.669841	0.75238	0.59102

The authors have trained these models for 50 epochs with callbacks to save computational power. As per Table 2, the authors have found that DenseNet169 and MobileNet are the ones that performed quite well with the present dataset. DenseNet169 shows the best accuracy, and loss value on the testing dataset. While MobileNet has shown the best precision and InceptionV3 shows the best recall values for the given test dataset. However, the overall performance of the MobileNet and DenseNet169 is better compared to the InceptionV3 model on the given data. In addition to that, the difference between the recall values of MobileNet-InceptionV3 and DenseNet169-InceptionV3 is not that significant compared to the accuracy and loss values of the same. Based on this analysis, the authors have proposed an ensemble model of MobileNet and DenseNet169 that performed well compared to all explored models.

3.4 Proposed Classification model

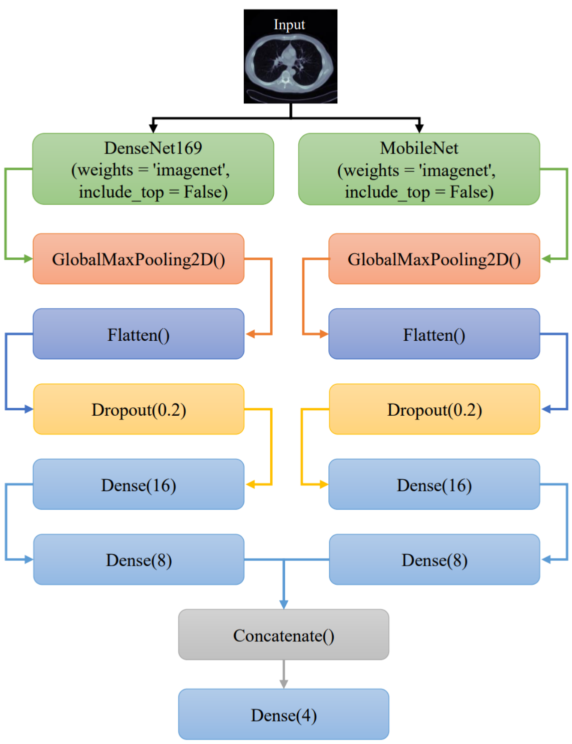


Figure 3: Proposed model

The authors have proposed an ensemble model of DenseNet169 and MobileNet, as Figure 3, with starting weights the same as "imagenet" and setting parameter include_top as False. The output of both of the models will be passed through a series of layers as shown in Figure 3. The series of layers are as follows: GlobalMaxPooling2D layer, followed by Flatten layer that will be passed to Dropout layer with 20% dropout ratio, and then finally two dense layers having 16 and 8 neurons, respectively. The output of both of the models will be concatenated and becomes 16 neurons which will be passed to the last output layer with four neurons (of Dense layer). The input of the proposed model is a CT scan image that will be fed to the proposed model and will at the end, the model will give the probability of each class. The model is complied with loss function as 'categorical_cross-entropy, optimizer as 'adam', and metrics as 'accuracy', 'precision', and 'recall'. As mentioned for the base models, the proposed model has early callbacks implemented to reduce the computational loads.

Table 3: Performance Parameters

Parameters	**Values**
Programming Language	Python 3.8.0
Platform	Google Colab
Framework	TensorFlow
Batch size	8
Epochs	50
Optimizer	Adam
Loss	Categorical cross-entropy
Metrics	Accuracy, Recall, Precision
ModelCheckpoint	monitor = Validation Accuracy

Table 3 shows the performance parameters set to experiment with the proposed setup and the base models. Table 3 shows the different sets of hyperparameters details as well as the details of the experiment environment. To reproduce the mentioned results, the environment setup with the values is shown in an opposite column.

4 RESULTS

Table 4: Proposed model performance's comparison with best performing models

Model	Loss	Accuracy	Recall	Precision
DenseNet169	0.547894	0.853968	0.93968	0.45963
MobileNet	0.559497	0.825397	0.93651	0.65121
InceptionV3	0.624704	0.793651	0.94286	0.44461
Proposed	**0.344487**	**0.873015**	**1**	0.58558

This section evaluates the performance of the proposed model with different base models for the given lung cancer CT scan dataset. To evaluate the performance of the proposed model, the authors have considered the loss function, accuracy, recall, and precision value on the test dataset which is the holdout dataset. The authors have considered the recall metric to be maximized for the defined objectives. To maximize the recall of the proposed model, the authors have trained the model with the training dataset and validated it on the validation dataset. Figure 4 shows the comparison of the loss values on the training and validation dataset for 50 epochs. In the same way, Figure 4 also shows the comparison of the accuracy values of training data and validation data for 50 epochs. In Figure 4 blue dot represents the best values on the validation dataset for loss and accuracy on the respective

Figure 4: Training-validation accuracy-loss comparison for proposed model

subgraphs. The lowest value of a loss on the validation dataset is 0.3280 while the highest accuracy achieved is 91.67%.

Table 4 compares the performance of the proposed model with the best-performing base models. The proposed model has the lowest loss value on the test dataset which is 0.344487 approx 30% less than the base model lonely-DenseNet169. On the other side, the overall accuracy of the test dataset is also improved from 85.3968% to 87.3015%. The recall value of the proposed model also becomes perfect at 1.0. However, the proposed model is not able to improve the value for metric precision and stay at approx 0.58. The performance also can be determined by the training time of the proposed model. The average training time of the proposed model also increases from 15 seconds/epochs to 18 seconds/epochs. The proposed models' size also becomes twice the base models and still being able to complete the per epoch training in 18 seconds is considered promising. As this is a medical domain, the domain-specific performance metrics would be recall value. Instead of accuracy or precision, the model should get better recall as better the recall system can easily identify the CT scans having lung cancer and that's the objective. The recall is more important as if any CT scan of a normal category is misclassified as a lung cancer scan then there's a way it can be cross-checked in the next stage of clinical analysis but if a CT scan of lung cancer is misclassified as a normal then there's a risk of life as no way to correct the mistake of misclassification. Hence, recall is the domain-specific metric and is focused more on improving recall values.

5 DISCUSSION

I got some basic ideas about an experiment through the reviewed literature. To understand the performance of the complex CNN model, I trained every model individually and analyzed their score on the test dataset. Then, I conclude that the DenseNet169 and MobileNet's ensemble should perform better comparing existing methods. I did train the model as described in the and found that the proposed ensemble model did perform well on the test dataset with promising results based on metrics such as recall, accuracy, and loss.

6 CONCLUSION

The authors have implemented deep-learning models to classify lung cancer from patients' CT scan images. The authors have proposed a model that was trained with very few numbers of a sample (1000) and stills achieves better performance than the existing models. The authors have handled the issue of the small dataset by augmenting the dataset in the pre-processing steps. Before proposing the model, the authors did an extensive literature review of the existing methods to classify lung cancer from CT scan images. The author has given a brief description of the dataset and explained the pre-processing done on the dataset. Then, the authors trained some basic models with the architecture shown in Figure 2. After analyzing the performance of the individual model on the test dataset, the authors have chosen two models for the ensemble as a proposed model. The proposed model is ensembled with two models DenseNet169 and MobileNet. The proposed model is trained for 50 epochs with the functioning of the callbacks. The proposed model outperformed the basic model individually for metrics such as recall, accuracy, and loss. The proposed model got an accuracy of 87.3015%, a recall value of 1, and the least loss value of 0.344487. Thus, the proposed model solves two major problems of accessibility of the data, and a better system that performs well to classify lung cancer.

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