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Lung Cancer Detection and Classification Using EfficientNet

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Abstract

Early prediction and classification of cancer stages are mandated to take countermeasures for treatment and easy diagnosis. The scanned images are mostly used to obtain the occurrence of lung small cell cancer. To diagnose lung cancer using EfficientNet we present a convolutional neural network to diagnose three types of lung cancer based on scanned images. The proposed model consists of the main path and three sub-paths. The main path works to extract the small features and creates feature maps at low-level. As for the sub-paths is responsible for transferring the medium and high levels feature maps to fully connected layers to complete the classification process, also the ResNet was prepared to compare it with the performance of the proposed. We use neural architecture search to design a new baseline network and scale it up to obtain a family of models, called EfficientNets. We systematically study model scaling and identify that carefully balancing network depth, width, and resolution can lead to better performance. Based on this observation, we propose a new scaling method that uniformly scales all dimensions of depth/width/resolution using a simple yet highly effective compound coefficient.

Keywords— *EfficientNet, Deep Learning, Convolutional Neural Networks, Lung Cancer Detection, ResNet, MobileNets*

I. INTRODUCTION

Lung cancer can cause severity to people of any gender or any age. In recent years, even young and middle-aged people were affected by this disease. In earlier 2016, the World Health Organization (WHO) collects and produces the reports as most critical cancer type among the top severe diseases like liver fungal cancer, severe gastric cancer, breast cancer, colorectal cancer, and stress esophagus cancer and which leads to death because it is complex to diagnose and treat the patients. Around 1.59 million people died due to lung cancer, according to the report. In 2018, it affected more men compared to women because it is usually caused by chain-smoking cigarettes and liquor drinking. Even more, this can also be affected through the genetic disorder.

As standards, lung cancer could be classified into 4 categories; they are as Adenocarcinoma, squamous carcinoma, tiny cell cancer, and large cell carcinomas. Usually, pathologists can diagnose lung cancer and its stages as a traditional approach. Almost computed tomography acquisition can be used for identification. However, they diagnose as much as possible, but it may be time-consuming and mislead to side effects. This can be avoided through the identification of severity based on their stage of lung cancer. It can be identified and predicted through the image processing operations over the CT images. The easy and effective prediction can be done through the implementation of DL techniques. Rather than the machine learning techniques, the DL can be obtained through the large sparse set of dataset representation. It can be effectively predicted through the huge set of training

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samples. The shape and texture features can be extracted and used for the implementation of classification. This can be achieved through the fully Convolutional neural network (CNN) to obtain the betterment results when compared to the CNNs. In existing, we had this same problem with the high number of convolutions over the implementations. Thus may obtain somewhat improved better results when compared to their existing works. Here, this implementation with proposed candidate generation in fully convolution neural network (FCN) with two phases such as screening and discrimination phase using the tools for detection, type-based. The model was proposed by Mingxing Tan and Quoc V.Le of Google Research, Brain team in their research paper 'EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

Based on this observation, they proposed a new scaling method that uniformly scales all dimensions of depth, width, and resolution of the network. They used the neural architecture search to design a new baseline network and scaled it up to obtain a family of deep learning models, called EfficientNets, which achieve much better accuracy and efficiency as compared to the previous Convolutional Neural Networks. They also presented a comparison of EfficientNet's performance with other powerful transfer learning models when worked on the ImageNet dataset. It has been shown that the latest version of EfficientNet that is EfficientNet-B7 has the highest accuracy among all with fewer parameters.

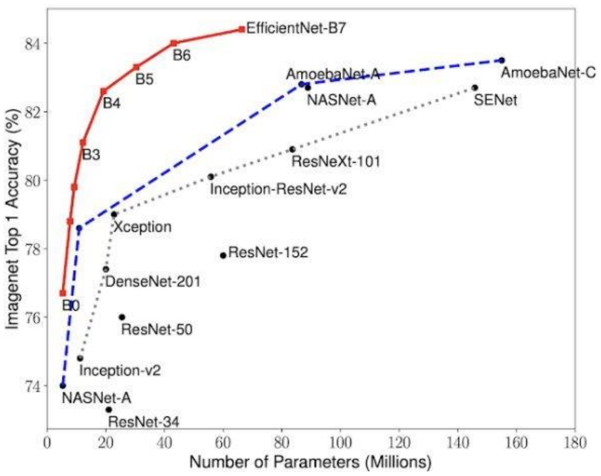

Figure 1: Efficient Net Performance

The graph below taken from the paper shows the performance curve of the EfficientNet family.

- It shows that for the same FLOPS, the accuracy of EfficientNet is higher than any existing architecture. So, if planning to use Inception-v2, one should consider using EfficientNet-B1 instead. Similarly, it is a good idea to consider EfficientNet-B2 if planning to use ResNet-50.
- In most real-world applications, people start with a pre-trained model and fine-tune it for their specific application.
- The good news is that the authors have done those experiments and shown when the EfficientNet backbone is used, we get better performance in other computer vision tasks as well.

CNN contrast EfficientNets and existing models, EfficientNet CNN model are better than the existing model, of higher accuracy, higher efficiency, and the number of its parameters FLOPS have dropped an order of magnitude, EfficientNet-B7 won the best currently on the ImageNet 84.4 % top-1 / 97.1% top-5 accuracy, and the CPU speed is 6.1 times Gpipe inference, the model size and aspect,

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EfficientNet-B7 is much smaller than other models, while also compared ResNet-50, accurate win a chip rate is (ResNet-50 76.3%, EfficientNet-B4 82.6%)[3].

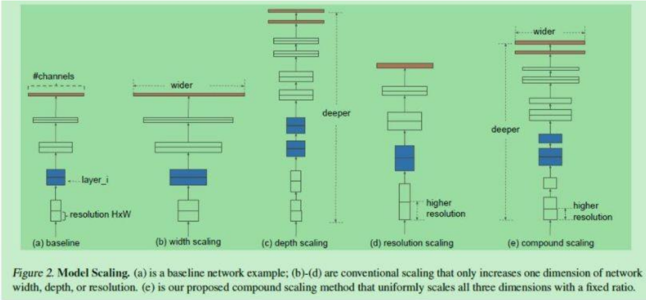

Figure 2: Scaling

Our three common network adjustments: receptive field increases w, increased network depth d, increases the size of resolution r, as a schematic view in three ways. Wherein,
(a) Is a baseline network, as may be appreciated that a small network;
(b) To increase the receptive field of network expansion mode;
(c) Mode network to increase the depth d of the extended network;
(d) Increase the resolution r for the extended network fashion;
(e) As set forth herein mixed-mode parameter expansion.

II. BACKGROUND

In this section, the background knowledge should be learned and analyzed through the discussions made. Thus, the in-depth details are discussed here. 2.1 Lung Cancer Data Collection: Lung cancer is a tumor-like disease affected in the spongy-like area of the lungs and it is the leading cause of cancer deaths. Lung cancer disease is probably caused by smoking, liquor drinking, and a genetic disorder. This can be categorized based on the tumor cells spread in the lungs and their area. This could be majorly classified into 2 varieties. They are tiny cell lung cancer as well as non-tiny cell lung cancer. Thus the non- tiny cell lung cancer has categorized as squamous carcinoma, Adenocarcinoma as well as huge cell carcinoma.

The FCN is usual CNNs like architecture, where the end layer named fully connected layer is changed to another layer called receptive field layer. Here the discrimination analysis can be done to detect and classify the data through the large context.

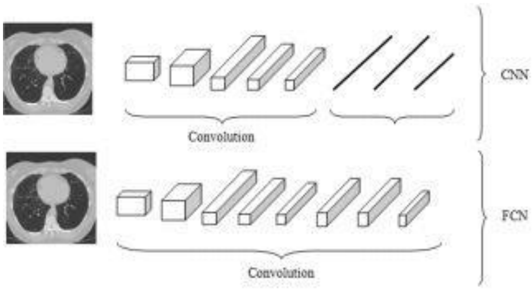

Figure 3: Conversion of Normal CNN to FCN

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The real conversion of normal CNN procedure to a fully convolutional neural network by replacing the fully connected layer throughout the convolution layer works. Over the past several years, image classification and object detection have seen tremendous improvements in accuracy as well as speed thanks to continued research into deep learning and convolutional neural networks (CNNs). The success and improvement found from deep learning are not from improved hardware and more encompassing datasets, but from innovations into model structure.

III. RELATED WORK

Many computer-aided systems have been developed to help radiologists better screen and classify lung cancer. We summarize these systems by the methods they adopt.

3.1 CNN-based Approaches

Ciompietal. used a convolutional neural network out-of-the-box where they extracted features from a CNN pre-trained on the ImageNet dataset and then applied a simple linear SVM classifier to classify peri-fissural nodules (a benign nodule in the lung with a high 2 false-positive rate in lung cancer detection). They used the ensemble of classifiers for 3D slices of an object to obtain the final classifier and compared its performance with a bag of frequencies descriptor with a similar accuracy of 86.8%. Hua explored a 3-layer CNN and a Deep Belief Network to approach the problem of nodule classification in computed tomography images. Sun et al considered three deep learning algorithms: CNN, Deep Belief Networks (DBNs), and Stacked Denoising Auto-encoder (SDAE) to classify nodules. They showed that the performance on down-sampled data of the three methods is similar and is around 80%.

3.2 Neural Network Approaches:

Many studies have focused on Artificial Neural Network approaches using an optimal combination of features. In particular, Kuruvilla and Gunavathi proposed an artificial neural network approach using statistical parameters like mean, standard deviation, skewness, kurtosis, fifth central moment, and sixth central moment to achieve the classification accuracy of 91.1%.

Abdulla et al. used area, perimeter, and shape as features to train an artificial neural network for the classification of lung cancer with a classification accuracy of 90%.

Other Image Processing Approaches: Image processing techniques have been greatly explored in nodule classification for lung CT images. Numerous studies adopted segmentation, morphological operations, and contour filter approaches for better nodule detection. Nathan and Kalyani developed a system to segment CT images and to classify focal areas in the lung region in real-time. They applied the adaptive threshold method and ROI processing to detect lung cancer with the least false-negative rate.

IV. PROBLEM STATEMENT

The project integrates different topics in Computer Science to try and solve a real-world problem in the medical domain. The project consists of CNN and software development to deliver a proof of concept. The application is a lung cancer detection system to help doctors make better and informed decisions when diagnosing lung cancer using Efficient Net.

V. LITERATURE REVIEW

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(1) Efficient Net: Rethinking Model Scaling for Convolutional Neural Networks, Mingxing Tan, Quoc V. Le, arXiv:1905.11946v5 [cs.LG] 11 Sep 2020, Convolutional Neural Networks (ConvNets) are commonly developed at a fixed resource budget, and then scaled up for better accuracy if more resources are available. This paper systematically studies model scaling and identifies that carefully balancing network depth, width, and resolution can lead to better performance. Based on this observation, it has been proposed that a new scaling method that uniformly scales all dimensions of depth/width/resolution using a simple yet highly effective compound coefficient. It demonstrated the effectiveness of this method on scaling up Mobile Nets and ResNet.

(2) Lung Cancer Prediction using Feed Forward Back Propagation Neural Networks with Optimal Features, International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 1 (2018), Dr. S. Senthil, B. Aishwarya. Initially, the Lung databases are collected and given as input to the system. Then data preprocessing is applied to the input images, for enhancing the image to get the high contrast images. The enhanced images are trained and tested by neural networks compared with sample training databases. Particle Swarm Optimization (PSO) is applied to extract the features of the given input images and a further process is proceeded to detect lung cancer.

(3) "Lung Cancer Detection Using Image Processing Techniques'' Shradha Fule, International Research Journal of Engineering and Technology (IRJET), Dec-2017 In this project, they access cancer images into MATLAB collected from different hospitals where present work is going on and this available image was a color image. Image quality and accuracy are the core factors of this research, image quality assessment as well as improvement are depending on the enhancement stage where low pre-processing techniques are used based on Gabor filter within Gaussian rules. The segmentation and enhancement procedure is used to obtain the feature extraction of normal and abnormal images. Relying on general features, a normality comparison is made. In this research, the main detected features for accurate image comparison are pixels percentage and mask-labeling.

(4) Lung Cancer Detection using Machine Learning, International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181 Published by, www.ijert.org RTICCT -2019 Conference Proceedings, Vaishnavi. D, Arya. K. S., Devi Abirami. T, M. N. Kavitha. This work has introduced one automatic lung cancer detection method to increase the accuracy and yield and decrease the diagnosis time. The goal is to classify the tissues into three classes of normal, benign, and malignant. In MR images, the amount of data is too much for manual interpretation and analysis. During the past few years, lung cancer detection in CT has become an emergent research area in the field of the medical imaging system.

(5) Deep convolutional neural networks for multi-planar lung nodule detection: Improvement in small nodule identification, Sunyi Zheng) and Ludo J. Cornelissen, Xiaonan Cui, Xueping Jing, 30 November 2020; f American Association of Physicists in Medicine, Inspired by clinical work, the paper aims to develop an accurate deep learning framework for nodule detection by a combination of multiple planes. Methods: The nodule detection system is designed in two stages, multi-planar nodule candidate detection, multi-scale false positive (FP) reduction. At the first stage, a deeply supervised encoder-decoder network is trained by axial, coronal, and sagittal slices for the candidate detection task. All possible nodule candidates from the three different planes are merged. To further refine results, a three-dimensional multi-scale dense convolutional neural network that extracts multi-

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scale contextual information is applied to remove non-nodules. In the public LIDC-IDRI dataset, 888 computed tomography scans with 1186 nodules accepted by at least three of four radiologists are selected to train and evaluate our proposed system via a tenfold cross-validation scheme. The free-response receiver operating characteristic curve is used for performance assessment.

VI. MOTIVATION

Lung cancer is one of the commonest cancers and causes of cancer-related deaths all over the world. It accounts for 13 percent of all new cancer cases and 19 percent of cancer-related deaths worldwide. There were 1.8 million new lung cancer cases estimated to occur in 2012. With this research, we would like to help doctors save time that is otherwise spent in the analysis of the CT Scans, for trying to identify Lung Cancer. This also indirectly saves precious time of the patient, which can otherwise be used for the treatment. We aim to build a system where the CT Scans be automatically analyzed using Efficient Net

VIII. ALGORITHM

STEP-1: Collect the lung cancer images from the respective cancer Dataset.

STEP-2: Analyze the dataset for the variety of lung cancer information present in the database.

STEP-3: Prepare the methodology for lung cancer detection model development and training-&-testing.

STEP-4: Prepare the dataset, with data augmentation for training.

STEP-5: Design the Deep CNN architecture to identify the Lung Cancer in the CT scan image. Train the model.

STEP-6: Train the CNN model and measure its performance. Finetune the algorithm if necessary

STEP-7: Create the system for using the trained DCNN model to identify lung cancer in new images.

VII. METHODOLOGY

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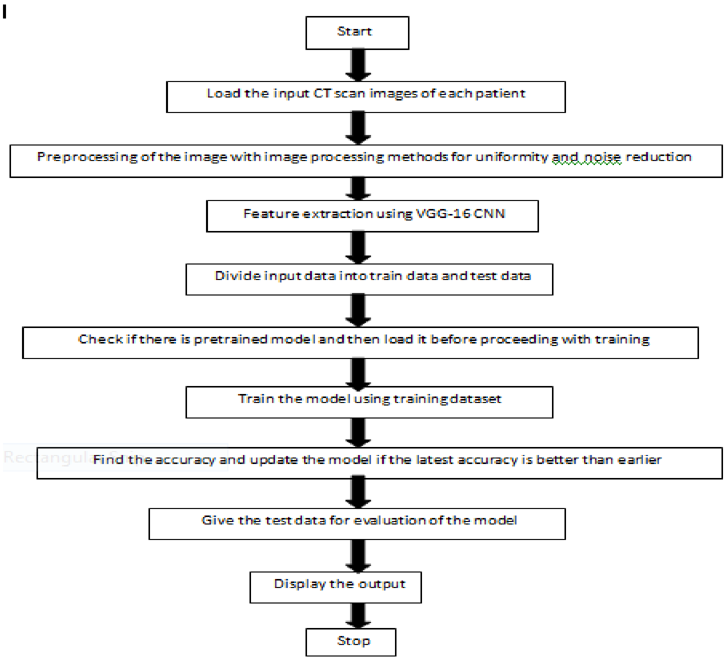

Figure 4: Flowchart of Methodology

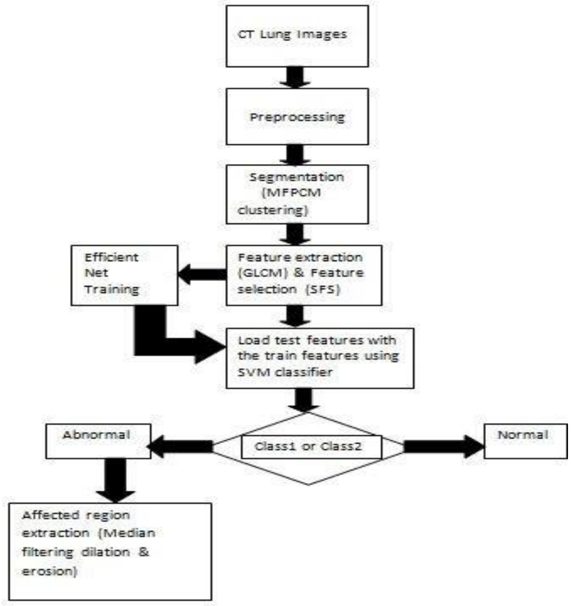

Figure 5: Algorithm Flow

A convolutional layer that extracts features from a source image A pooling layer that downsamples each feature to reduce its dimensionality and focus on the most important elements.

A fully connected layer that flattens the features identified in the previous layers into a vector, and predicts the probability that the image belongs to each one of several possible labels Convolutional Neural Networks (CNN) is a deep model that performs well with a variety of tasks such as image classification, natural language processing, and signal processing. CNN's are explicitly designed to deal with multi-dimensional input and overcome the high number of parameters that are requested by

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standard FNN. For example, a single RGB image of size 64x64, in an FNN would require: 64 • 64 • 3 = 12288 neurons as input. The issues that arise when the FNN is over parameterized are the following:

A huge number of input neurons will require more layers at a high computation cost and time required for training. Over parameterization is a symptom of overfitting: in the specific case of an image, the FNN would behave too meticulously since it will take into account every single pixel.

Convolutional layers convolve the input and pass its result to the next layer. This is similar to the response of a neuron in the visual cortex to a specific stimulus. Each convolutional neural processes data only for its receptive field]. Although fully connected feed-forward neural networks can be used to learn features as well as classify data, it is not practical to apply this architecture to images. A very high number of neurons would be necessary, even in shallow (opposite of deep) architecture, due to the very large input sizes associated with images, where each pixel is a relevant variable [8,16,26].

When programming a CNN, the input is a tensor with shape (number of images) x (image height) x (image width) x (input channels) [5, 24, 22]. Then after passing through a convolutional layer, the image becomes abstracted to a feature map, with shape (number of images) x (feature map height) x (feature map width) x (feature map channels). A convolutional layer within a neural network should have the following attributes:

- Convolutional kernels defined by a width and height
- The number of input channels and output channels
- The depth of the Convolution filter of the input channels must be equal to the number of channels of the input feature map.

Max pooling: Combining TDNNs with max-pooling to realize a speaker-independent isolated word recognition system; in their system, they used several TDNNs per word, one for each syllable. The results of each TDNN over the input signal were combined using max-pooling and the outputs of the pooling layers were then passed on to networks performing the actual word classification.

The convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels), which have a small receptive field but extend through the full depth of the input volume.

During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the entries of the filter and the input and producing a 2-dimensional activation map of that filter. As a result, the network learns filters that activate when it detects some specific type of feature at some spatial position in the input.

Pooling layer: Another important concept of CNNs is pooling, which is a form of non-linear down-sampling. There are several nonlinear functions to implement pooling among which max pooling is the most common. It partitions the input image into a set of non-overlapping rectangles and, for each such sub-region, outputs the maximum.

The pooling layer operates independently on every depth slice of the input and resizes it spatially. The most common form is a pooling layer with filters of size 2×2 applied with a stride of 2 downsamples at every depth slice in the input by 2 along both width and height. In addition to max pooling, pooling units can use other functions, such as average pooling or ℓ2- norm pooling. Average pooling was often used historically but has recently fallen out of favor compared to max pooling, which performs better in practice

IX. Conclusion

The model higher accuracy using the dice coefficient on the training set. The dice coefficient is much lower on the training set however the confusion matrix outputs a high true and false positive

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rate on a set that contains positive and negative samples. This indicates that the model is great at distinguishing between CT scan slices with no cancer nodules compared to the ones with cancer. I believe with more hyperparameter tuning and model training the accuracy could be increased.

X. FUTURE WORK

Soon, the system will be trained with large datasets to diagnose the type of cancer with its size and shape. The overall accuracy of the system can be improved using 3D Convolutional Neural Network and also by improving the hidden neurons with deep networks.

XI. ACKNOWLEDGEMENT

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