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An Ensemble Technique of CNN for Lung Cancer Identification

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***Abstract*—Lung cancer is one of the leading contributing factors to the mortality rate. The prevailing types of Non-small Cell Lung Cancer (NSCLC) include Adenocarcinoma, Large Cell Carcinoma and Squamous Cell Carcinoma. Studies have shown that 18% of the mortality rate stems from this disease. This is attributable to substandard diagnosis techniques and inefficient treatments available to cure metastasis. Hence, this paper opts to employ transfer learning techniques by using different state-of-the-art, pre-trained models to detect lung cancer and classify it into four groups, namely, Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma and Normal using chest CT scan images, followed by conducting a comparative analysis of their performances. The models implemented are Resnet101, VGG16 and InceptionV3 and DenseNet169. Moreover, the paper proposes a new CNN model using the ensemble technique which is an amalgamation of ResNet101 and InceptionV3 that are employed initially. In addition to that, it introduces another 11 layered CNN model built from the outset. The dataset used for this study is called Chest CT-Scan images which is retrieved from Kaggle. The models' performances are analysed utilizing different metrics like accuracy, precision, recall, F1-Score and AUC. The Ensemble of ResNet101 and InceptionV3 models has achieved the highest accuracy of 93.7%, on this particular dataset.**

***Index Terms*— NSCLC, CNN , RNN , ANN, KNN , AI, Lung Cancer, Machine Learning**

I. Introduction

Lung Cancer is a fatal disease that can potentially terminate lives. In the United States, lung cancer accounts for roughly 225,000 cases, 150,000 deaths, and 12 billion dollars in health-care costs per year [1]. It occurs when lung cells begin to mutate and uncontrollably divide, killing the surrounding healthy cells. If the cancer is metastatic then it will disseminate to other parts of the body. This paper specializes in detecting Non-Small Cell Lung Cancer (NSCLC) which can be divided into three categories, namely, Adenocarcinoma, Large Cell Carcinoma and Squamous Cell Carcinoma. Adenocarcinoma is the most common form of NSCLC, contributing to about 40% of lung cancer deaths [2]. It begins in cells that ordinarily exude substances like mucus [3]. Accordingly, Adenocarcinoma forms in the alveoli, hampering the gas exchange process. Large Cell Carcinoma is known for its atypical, large cells, infesting almost every inch of the lungs. It can grow and spread faster than the other two types of NSCLC. Lastly, Squamous Cell Carcinoma can be relatively more malignant as most cases manifest in the final stages [4]. It infects the bronchi, causing about a quarter of deaths from lung cancer. Technical advancements like Artificial Intelligence and Deep Learning plays pivotal roles in the detection of lung cancer. Pulmonary nodule screening is tedious and requires a great deal of attention to avoid missed diagnosis. Combining CAD and manual diagnosis significantly improves the screening process and allows very little space for error. In fact, it has been proven that using CAD for detection brings about better results than manual diagnosis, owing to its high sensitivity and specificity. Therefore, deep learning not only develops the lung cancer detection process but also sets a better picture for prognosis, leading to reduced mortality rates [5]. The use of Artificial Intelligence is widespread, mainly in medical image segmentation, pathological diagnosis of lung cancer, extraction of lung nodules and searching the tumour marker in lung cancer detection. Convolutional Neural Network (CNN), a domain of Deep Learning is the most common algorithm used for image recognition and classification. It has been dominating the machine vision space for many years. In fact, the best performances for many databases such as MNIST database (99.77%), CIFAR10 dataset (97.6%) and the NORB database (97.47%), was drastically improved with research conducted using CNN [6]. A CNN model typically has an input layer, output layer, convolution layers, pooling layers, fully connected layers and Normalisation layers (ReLU) [7]. For more complicated models, additional layers can be employed. Having this array of well-trained networks, CNN is able to efficiently utilize millions of images being fed to it and bring about outstanding results that surpass the previous success [8]. Furthermore, research has proven that CNN works better than its competitors; RNN (Recurrent Neural Network), KNN (k-Nearest Neighbours) and ANN (Artifical Neural Network), as CNN has the ability to detect important features of images automatically, without the need for manual supervision [9].

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II. Objectives

This paper attempts to pursue the following objectives to conduct a thorough comparative analysis.

i. Employ five pre-trained CNN models and one self constructed model:

Previous researches simply used at most two model for the diagnosis. This paper employs five pre-trained models and a self constructed model that can automatically classify and detect important features of images without the need of human supervision for efficient lung cancer diagnosis.

ii. Conduct a Comparative Analysis on the performances of the models:

Previous researches did not perform a comparative analysis on the single model used with other existing models. Therefore, after employing the six models, the paper seeks to perform a comparative analysis on the results that the models yield.

iii. Determine the Best Working Models:

After doing a comparative analysis, the best working model is to be determined based on accuracy and other performance metrics. This can aid in hospitals deciding which model to use for lung cancer diagnosis.

iv. Design an Ensemble Model with the Best Working Models:

Using the Ensemble technique, the best working models are to be merged in order to create a new powerful model that can detect and classify lung cancer more accurately.

III. RELATED WORKS

The first paper written by Basha et al. [10], applied an enhanced Neural Network based algorithm for predicting lung cancer more accurately in the initial stage. They used the Chest CT-Scan Images dataset from Kaggle. For lung cancer image prediction PSO is used to combine CNN and ELM. Moreover, to improve the accuracy of detecting early stage diagnosis, the authors suggested the Optimized Extreme Learning Machine (OELM) model. Compared to existing models such as CNN, ELM and ANN, it is clear that the proposed OELM offers higher accuracy, specificity, sensitivity and precision.

In the next study [11], Han et al. utilized a common CNN model known as VGG-16, to detect lung cancer. This paper also made use of the Chest CT-Scan Images dataset from Kaggle. The proposed model was trained to categorize CT Scan images into four sectors to identify different types of lung cancers. The trained model was then coupled with a chatbox and a graphical user interface. Additionally, the scientists employed a variety of algorithms with various batch sizes to increase the accuracy of lung cancer detection. As a result, it was demonstrated that the proposed 64 batch-size self-designed CNN algorithms outperformed the competition by displaying higher accuracy. The researchers proclaimed to create a website for early lung cancer detection in the near future.

The Chest CT-Scan Images dataset from Kaggle was then classified into four forms of lung cancer by Sari et al. [12] using a modified ResNet50 architecture and transfer learning technique. After the modification of ResNet50 architecture it showed high accuracy of 93.33% and a sensitivity, precision, F1-score of 92.75%, 93.75% and 93.25% respectively. Furthermore, EfficientB1 and AlexNet were being compared with the modified ResNet50 architecture and it showed that the latter worked best during the mathematical analysis. However, they believe that if deep learning method is implemented, they can get better results in identifying lung cancer and other multivariate lung diseases.

The final research [13], Sasikala et al. proposed a method that employs CNN to detect malignant or benign tumours in the lung using CT images. The proposed framework is able to distinguish the presence and non-appearance of cancerous cells with an exactness of about 96%. In addition, 100% specificity was acquired in the study which depicts zero false positive detection. However, by comparing with prior CNN based systems, their proposed model performed better in terms of accuracy, specificity and sensitivity. For future research, large datasets will be used to train their proposed model for identifying the size and shape of lung cancer. Besides, 3D CNN including the hidden neurons with deep networks help to enhance the overall accuracy of their suggested method.

IV. PROPOSED METHOD

This paper utilizes five pre-trained models, namely VGG16, ResNet101, InceptionV3 and DenseNet169 and conducts transfer learning to observe their functioning. Moreover, it proposes a new CNN model built from scratch and a model made using the ensemble technique, that combines the two best pre-trained models. The dataset contains images of Adenocarcinoma, Large Cell Carcinoma and Squamous Cell Carcinoma. All of these are fed into each model so they can determine and allocate the images into their respective categories. Using the results obtained, a comparative analysis is made to determine the best performing model in terms of accuracy and other performance metrics. Figure 1 depicts the full workflow of the methodology.

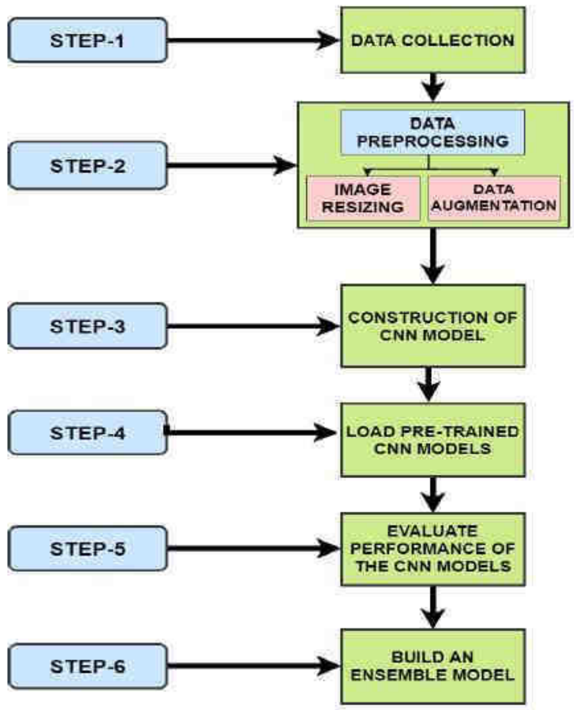

Fig. 1: Workflow of the methodology.

A. *Data Collection*

The Chest CT-Scan Images Dataset in PNG format from Kaggle [14] is used for this paper. The owner of the dataset collected these images from various sources for a cancer detection project of their own. It consists of four types of cancer images, namely, Adenocarcinoma, Large Cell Carcinoma, Squamous Cell Carcinoma and normal CT-Scan images. The data is already split into three categories that are training (70%), testing (20%) and validation (10%).

B. Data Pre-processing

Image transformation tasks, in which the input and output are both images, are important in a wide range of applications, including edge detection, semantic segmentation, and black-and-white image colorization [15]. Hence this method is used to eliminate unnecessary details of images that do not play a part in enhancing the accuracy of models. In fact, it enriches the valuable aspects of the raw data, productively contributing to the performance of the CNN models [16].
This paper refines data in two parts: Image Resizing and Data Augmentation. Images found in the dataset are of random sizes [17]. This inconsistency can potentially bring down the models' accuracy. Hence all the images are resized to 224x224 pixels before being fed to the models. In addition, Data Augmentation is carried out on the dataset to help remove sparse data [18]. This technique manually modifies the dimensions of the training dataset, producing multiple altered copies of the selected images. The following geometric modifications are applied: Rescale, Range, Rotation, WidthShiftRange, HeightShiftRange, HorizontalFlip and VerticalFlip.

C. CNN Model Construction

A new CNN model of 11 layers is constructed for further comparison. This comprises of Convolution layer, Pooling layer and Fully-Connected layer. Apart from that, Dropout layer is also added to enhance the efficacy of the model. The layers are described in more details below :
1. **Convolutional Layer:** Four layers of Conv2D is selected for this layer.
2. **Pooling Layer:** This consists of three Maxpooling2D layers that calculates the maximum value of each feature map.
3. **Fully Connected Layer:** This layer is composed of two additional layers. The Flatten layer is used after selecting the pooling layer to level out the entire network. After this, two dense layers are applied so that the outputs from the previous layers are fed as inputs to all the model's neurons. This helps to reduce computational complexity, which in turn, accelerates the training time.
Table 1 depicts the summary of the newly constructed CNN model.

Table 1: Summary of the 11 layered CNN model

Layer (type)	Output Shape	Param
conv2d (Conv2D)	(None, 222, 222, 32)	896
$conv2d_1(Conv2D)$	(None, 220, 220, 32)	9248
$max_pooling2d(MaxPooling2D)$	(None, 110, 110, 32)	0
$conv2d_2(Conv2D)$	(None, 108, 108, 64)	18496
$max_pooling2d_1(MaxPooling2$	(None, 54, 54, 64)	0
$conv2d_3(Conv2D)$	(None, 52, 52, 128)	73856
$max_pooling2d_2(MaxPooling2$	(None, 26, 26, 128)	0
dropout (Dropout)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 64)	5537856
$dense_1(Dense)$	(None, 4)	260

D. Loading of Pre-trained model

The Keras library is employed to load the pre-trained models for transfer learning. This is a robust and user-friendly, deep learning Application Programming Interface that is written in Python [19]. It facilitates simple training of neural network models in merely a few lines of code by encasing the structured numerical computational libraries, Theano and TensorFlow. The following is a list of the models that are used in this study:
I. **ResNet101**
II. **VGG16**
III. **InceptionV3**
IV. **DenseNet169**
The selection of these pre-trained models was predicated from the potential to achieve consequential accuracy in classifying lung cancer from CT scan images. It has been proven that VGGNet and ResNet are able to identify modalities of medical images more accurately as they have different depths of pre-training on ImageNet [20]. In contrast, other experiments substantiate that training deep learning models with transfer learning from ImageNet-pretrained CNN models, tend to yield significant accuracy at classifying medical images [21]. These CNN models include DenseNet and Inception. Hence, this study resorts to take at least one variant from each of these CNN models to make the selection as diverse and versatile as possible. This in turn, can help put forward a good comparative analysis of their performances in detecting lung cancer from chest CT scan images.

E. Ensemble Model

After training and testing the pre-trained models individually, it was found that ResNet101 and InceptionV3 performs well for detecting lung cancer on this dataset. These models have achieved an accuracy of 90.95% and 91.74% respectively.
With a view to achieve better performance than the pre-trained models, this study has opted to build an ensemble model of the best two performing models. In order to do so, the outputs of both resnet101 and inceptionV3 have been put in a concatenation layer. Following that, an extra dense layer was added, followed by another dense layer with a single output and an activation function,'Softmax,' as this study involves multi-class categorization. The accuracy of this new ensemble model is 93.71%, which is an increase of 1.97% precisely.

V. EXPERIMENTAL RESULTS

The accuracy of DenseNet-169, InceptionV3, Ensemble (Resnet-101+InceptionV3), ResNet-101, VGG-16 is 88.96%, 91.74%, 93.70%, 90.95%, 82.77% respectively which is shown in Table 2, along with other evaluation metrics like precision, recall, AUC and F1 score. We found out that models with more layers tend to have better accuracy even though InceptionV3 is an exception but the trend we see is that the more the number of layers and the denser the architecture, the better the accuracy. Amongst all the transfer learning models, the combined model of Resnet-101 and InceptionV3 works best with a considerable amount of parameters. The accuracy reached by the combined model is a state-of-theart accuracy for this particular dataset. However, our proposed ensemble model also has an accuracy of 93.7%

which is a competitive accuracy compared to the state-of-the-art models that are used. Table 2 below shows a comparison of all the models' performances.

Model	Accuracy	Precision	Recall	AUC	F1Score
Ensemble (Resnet101+Inceptionv3)	93.70 %	83.85 %	82.27 %	95.50 %	82.45 %
Inception V3	91.74 %	83.92 %	82.83 %	95.72 %	83.39 %
Resnet101	90.95 %	84.30 %	78.41 %	95.49 %	81.24 %
DenseNet 169	88.97 %	78.20 %	77.46 %	93.88 %	77.83 %
Vgg16	82.78 %	89.52 %	35.24 %	86.74 %	50.57 %
New CNN Model	72.94 %	45.78 %	44.76 %	78.72 %	45.26 %

The figure below depicts both train and validation accuracy and train and validation loss of the Ensemble model. Here, it can be seen that the training and validation accuracy are converging with one another at a good rate, indicating that there is neither any overfitting nor any underfitting. It further signifies how powerful the ensemble model is at this particular classification. On the other hand, the training and validation loss graph represents that loss is getting lower as the model is moving forward with the training and it stops at almost zero (0) which again implies the strength of the model.

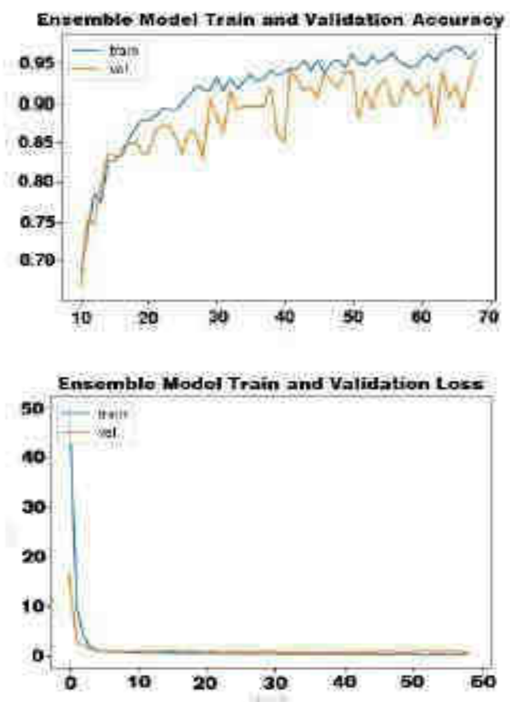

Fig. 2: Train & Validation Accuracy and Train & Validation Loss of the Ensemble Model.

VI. Conclusion and Future works

Lung cancer is a leading cause of death worldwide. In order to reduce the severity of cases, a meticulous diagnosis is required. But the present day detection methods are quite ineffective and tedious. This paper aims to improve the detection of cancer using a powerful CNN model. The research also employs the ensemble technique to combine two CNN models into one and evaluate their performance. The secondary aim of the paper was to do a comparative study on the effectiveness of different CNN models. Since previous researchers aimed to only analyze the best-suited model, this paper aims to find the reason behind the model's yield performance. The ensemble model proves to have the highest accuracy of 93.7%. The accuracies of the other CNN models was lower than the ensemble model. DenseNet169, InceptionV3 and ResNet101 were 88.97%, 91.74% and 90.95% respectively. In the near future, the paper seeks to apply Meta Learning and design not only a more powerful CNN model that can yield a higher accuracy, but also a model that has the potential to be employed commercially in the detection of lung cancer.

References

[1] W.-J. Choi and T.-S. Choi, "Automated pulmonary nodule detection system in computed tomography images: A hierarchical block classification approach," *Entropy*, vol. 15, no. 2, pp. 507–523, 2013.
[2] M. J. Legato and J. P. Bilezikian, *Principles of gender-specific medicine*. Gulf Professional Publishing, 2004, vol. 2.
[3] L. H. Araujo, L. Horn, R. E. Merritt, K. Shilo, M. Xu-Welliver, and D. P. Carbone, "Cancer of the lung: Non–small cell lung cancer and small cell lung cancer," in *Abeloff's clinical oncology*, Elsevier, 2020, pp. 1108–1158.
[4] F. Lonardo, V. Rusch, J. Langenfeld, E. Dmitrovsky, and D. S. Klimstra, "Overexpression of cyclins d1 and e is frequent in bronchial preneoplasia and precedes squamous cell carcinoma development," *Cancer research*, vol. 59, no. 10, pp. 2470–2476, 1999.
[5] F. Perla, R. Richman, S. Scognamiglio, and M. V. Wüthrich, "Time-seriesforecasting of mortality rates using deep learning," *Scandinavian Actuarial Journal*, vol. 2021, no. 7, pp. 572–598, 2021.
[6] Q. Li, W. Cai, X. Wang, Y. Zhou, D. D. Feng, and M. Chen, "Medical image classification with convolutional neural network," in *2014 13th international conference on control automation robotics & vision (ICARCV)*, IEEE, 2014, pp. 844–848.
[7] M. Hussain, J. J. Bird, and D. R. Faria, "A study on cnn transfer learning for image classification," in *UK Workshop on computational Intelligence*, Springer, 2018, pp. 191–202.
[8] N. Sharma, V. Jain, and A. Mishra, "An analysis of convolutional neural networks for image classification," *Procedia computer science*, vol. 132, pp. 377–384, 2018. [9] A. Dertat, "Applied deep learning-part 4: Convolutional neural networks," *Towards Data Science*, 2017.
[10] B. M. F. Basha and D. M. M. Surputheen, "Optimized extreme learning machine based classification model for prediction of lung cancer," in *International Journal of Electrical Engineering and Technology (IJEET)*, IAEME, 2020, pp. 323–332.
[11] Z. Han, L. Liu, Y. Liu, and H. Mao, "Diagnose lung cancer and humanmachine interaction based on cnn and nlp,"

in *2021 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT)*, IEEE, 2021, pp. 175–179.

[12] S. Sari, I. Soesanti, and N. A. Setiawan, "Best performance comparative analysis of architecture deep learning on ct images for lung nodules classification," in *2021 IEEE 5th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, IEEE, 2021, pp. 138–143.

[13] S. Sasikala, M. Bharathi, and B. R. Sowmiya, "Lung cancer detection and classification using deep cnn," in *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, IJTTEE, 2018, pp. 259–262.

[14] M. Hany, *Chest ct-scan images dataset*, Aug. 2020. [Online].
Available:https://www.kaggle.com/datasets/mohamedhanyyy/chest- ctscanimages.

[15] V. J. Gomes, K. A. Alavee, A. Sarda, Z.-E. Akhand, *et al.*, "Early detection of diabetic retinopathy using deep learning techniques," Ph.D. dissertation, Brac University, 2021.

[16] S. Tang, S. Yuan, and Y. Zhu, "Data preprocessing techniques in convolutional neural network based on fault diagnosis towards rotating machinery," *IEEE Access*, vol. 8, pp. 149 487–149 496, 2020.

[17] S. Saponara and A. Elhanashi, "Impact of image resizing on deep learning detectors for training time and model performance," in *International Conference on Applications in Electronics Pervading Industry, Environment and Society*, Springer, 2022, pp. 10–17.

[18] A. I. Rahman, S. Bhuiyan, Z. H. Reza, J. Zaheen, and T. A. N. Khan, "Detection of intracranial hemorrhage on ct scan images using convolutional neural network," Ph.D. dissertation, Brac University, 2021.

[19] J. Brownlee, *Your first deep learning project in python with keras step-bystep*, Oct. 2021.

[20] Y. Yu, H. Lin, J. Meng, X. Wei, H. Guo, and Z. Zhao, "Deep transfer learning for modality classification of medical images," *Information*, vol. 8, no. 3, p. 91, 2017.

[21] G. An, M. Akiba, K. Omodaka, T. Nakazawa, and H. Yokota, "Hierarchical deep learning models using transfer learning for disease detection and classification based on small number of medical images," *Scientific reports*, vol. 11, no. 1, pp. 1–9, 2021.

[22] E. Hussain, M. Hasan, S. Z. Hassan, T. H. Azmi, M. A. Rahman, and M. Z. Parvez, "Deep learning based binary classification for alzheimer's disease detection using brain mri images," in *2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, IEEE, 2020, pp. 1115–1120.

[23] S. Das, O. R. R. Aranya, and N. N. Labiba, "Brain tumor classification using convolutional neural network," in *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*, IEEE, 2019, pp. 1–5.

[24] S. Narkhede, "Understanding auc-roc curve," *Towards Data Science*, vol. 26, no. 1, pp. 220–227, 2018.