Automated Lung Cancer Detection Using Convolutional Neural Networks from Chest CT Image Datasets

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***Abstract*—Lung cancer is one of the top diseases causing the death worldwide due to very late-stage diagnosis and its high mortality. Early detection is critical for improving patient outcomes, as the survival rate significantly decreases when the cancer spreads beyond the lungs. The aim of this research is to develop an automated and efficient lung cancer system using deep learning algorithms applied to medical imaging data, including X-rays and CT scans. This study utilized the Lung Imaging Database Consortium-Image Database Resource Initiative (LIDC-IDRI) dataset, consisting of 900 images, divided into 57% for training, 35% for testing, and 8% for validation. The proposed system employs the ResNet 50 model, using the Stochastic Gradient Descent with Momentum (SGDM) optimization technique. The experimental results demonstrated that ResNet 50 consistently outperformed Inception mv4 across all metrics. ResNet 50 achieved perfect diagnostic accuracy, with minimal losses, whereas Inception mv4 showed lower accuracy and higher losses. These findings indicate that the ResNet 50 model offers superior diagnostic accuracy and efficiency for early lung cancer detection, highlighting its potential for clinical application to improve patient outcomes and reduce mortality rates.**

***Index Terms*— *keyword; keyword;* Lung Cancer, Medical Images, Deep Learning, Convolutional Neural Networks, ResNet, Inception MV4.**

I. INTRODUCTION

Lung cancer constitutes the predominant cause of cancer-related fatalities globally, characterised by a significant mortality rate attributable to late-stage diagnosis. Lung cancer arises when lung cells proliferate uncontrollably, resulting in the formation of a tumour [1]. Over time, the tumour may metastasis to other regions of the body, including the lymph nodes and various organs. There are two predominant forms of lung cancer which are Small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC) [2]. Non-small cell lung cancer (NSCLC) is the predominant type of lung cancer, representing approximately 85% of all instances. SCLC is less prevalent; however, it proliferates and metastasises more rapidly than NSCLC.

According to the World Health Organization (WHO)[3], lung cancer will account for more than 1.8 million cancer-related deaths globally in 2020. Lung cancer is more prevalent in men than in women, with the highest incidence occurring in individuals aged 65 and above. While smoking is one of the predominant reasons of lung cancer, additional factors such as air pollution , asbestos, radon, and can significantly elevate the risk.

Early-stage detection of lung cancer is essential to improving patient outcomes and reducing mortality rates. Roughly 56% of the patients diagnosed with localised disease (confined to the lungs) were alive for five years [4]. Additionally, the lung cancer cases are identified at an early stage is only 16%. The five-year rate of survival for metastatic tumours is below 5%. Consequently, lung cancer early identification can markedly enhance the prospects for successful treatment and prolonged survival. CT scans are routinely used for lung cancer screening, however diagnosing lung cancer from these pictures is time-consuming and needs skill.

This research aims to create an automated system for early detection lung cancer utilising deep learning algorithms and medical imaging data, including CT scans and X-rays. We will employ a variety of deep learning techniques and models, tune them, and assess their accuracy and efficiency. The ultimate aim of the project is to develop a reliable and accurate automated lung cancer detection system that can be used in clinical practice to aid in the early detection and diagnosis of lung cancer. Establishing such a system successfully might have a significant impact on public health by improving patient outcomes, cutting healthcare costs, and saving lives.

II. LITERATURE REVIEW

Lung cancer is one of the top diseases causing the death worldwide due to very late-stage diagnosis and its high mortality.. Recent years have witnessed considerable research focused on the advancement of novel techniques for lung cancer detection. This review and study of the literature will look at some of the relevant studies on lung cancer detection.

Vas, M., & Dessai, A. [5] proposed a method for developing an automated system for lung cancer detection from CT images. Pre-processing, separation or segmentation, feature extraction, and classification are the four different steps of the system. Cropping photos and applying the Median filter are part of the pre-processing procedure. Complementing the pictures and opening operation using periodicline SE, filtering using maximum area, and closing operation using disc SE are all part of the segmentation process. The feature extraction process begins by resizing the image into three distinct resolutions, followed by Haar Wavelet transformations. The GLCMs are then computed, and the Harlick features are extracted. An ANN is then used to classify the retrieved features. The model achieved 92% accuracy.

Jena, S. R., George, T., & Ponraj, N. [6] suggested technique created a texture-based model for lung cancer identification. The model extracts feature from preprocessed image data. The characteristics are generated according to shape, texture, and intensity. The extracted texture characteristics are analysed using a local binary pattern. The characteristics are categorised using an SVM classifier. The algorithm accurately categorised the test data of 40 photos each of normal and cancer-affected images.

Zhang et.al [7] study used the LIDC dataset and data preprocessing and augmentation techniques to enlarge the pulmonary nodule sample library. Then, it is used in the training stage of a Convolutional Neural Network (CNN) model to find patterns, divide pulmonary nodules into segments, get the size of each segment, and use the size form of pulmonary nodules to identify lung cancer. The suggested model, which is based on a convolutional neural network incorporating morphological features, has given better accuracy.

Nawreen, et.al. [8] developed a methodology for detecting lung cancer using CT scan data. They employed edge detection and thresholding to divide the lung tumour's area of interest (ROI). Using a support vector machine (SVM) classifier, the extracted ROI is categorised as malignant or benign based on geometrical features. The model is highly accurate in detecting lung cancer nodules and estimating the severity level.

Sakr, A. S. [9] proposed a streamlined deep learning methodology utilising convolutional neural networks (CNN) for the effective diagnosis and identification of lung cancer. The approach employed normalised histopathology images to train the CNN model, which detects lung cancer. The model is examined and compared to existing cancer detection methods. An accuracy of 0.995 percent was achieved by the proposed deep model for lung cancer diagnosis, surpassing that of previous methods.

Firdaus et.al. [10] developed detection method for lung cancer based on CT-scan pictures. There are four main steps to this detection method: pre-processing of CT-Scan images, cancer object segmentation from background, and feature extraction using area, energy, contrast, homogeneity, and entropy as criteria. Two main categories are there of lung cancer: malignant and benign. A precision of 83.33% is achieved by the system.

Saric et.al. [11] proposed a deep learning-based approach for lung cancer cells detection in lung tissue WSIs (whole slide histopathology images). The region of interest, which contains tissue in the WSI region, is extracted as the first step (ROI). The tissue region is defined as an area with a grey level less than 0.8. The ROI is then used to create training samples. If 75% of the pixels in the patch are identified as tumour, the patch is labelled as tumour. Subsequently, two CNN architectures, VGG16 and Resnet50, are employed for patch classification, and their results are compared. The VGG16 performed marginally greater in terms of patch classification accuracy and AUC.

Bushara A. R. and Vinod Kumar R. S. [12] employed Convolutional Neural Networks (CNN) to recognize cases of Lung cancer. To improve a Convolutional Neural Network's accuracy, an augmentation strategy has been suggested. By applying various transformations like scaling, rotation, and contrast modification, data increment is used to find the proper training samples from existing prior training sets. The networks are evaluated using the LIDC-IDRI database. Overall, the proposed work showed a 95% success rate. When it comes to benign test data, the F1 score is 0.95, the recall is 0.96, and the precision is 0.93. The accuracy, F1 score, and recall for tumour data are 0.96, 0.93, and 0.95, in the respective order. When compared to other cutting-edge methodologies, the proposed system shows impressive results..

III. MATERIALS AND METHODS

A. Dataset

The Lung Imaging Database Consortium-Image Database Resource Initiative (LIDC-IDRI) dataset is collaboratively produced by the LIDC and IDRI, encompassing a total of 1010 subjects. The data is available publicly for researchers in DICOM format, accompanied by the radiologists' annotations in XML markup. The annotations cover each object within the lung region of the LDCT that was identified as a nodule by a radiologist, as well as the coordinates and the number of radiologists who annotated each nodule [13]. Every image uses DICOM format, which has pixels as small as 512 x 512 and slices ranging from 1.25 to 2.5 mm in width. In LIDC-IDRI, the thickness runs from 0.48 mm to 0.72 mm [14]. Four radiologists have noted several criteria including lesion size, type of tumour, and location [15]. From nodules less than 3 mm in diameter, non-nodules, or nodules greater than 3 mm in diameter, all images in the LIDC datasets were categorised as either A benign nodule was determined for the proposed study as one with a diameter less than 3 cm; a malignant nodule was defined as one with a diameter more than 3 cm [12].

The initial proceeds in developing and training a convolutional neural network for classifying lung images as malignant benign or is the acquisition and preparation of the datasets. Following the download of the datasets from the LIDC - IDRI data sets, the images are replicated into the three directions, train, test, and validate including malignant and benign directories. 900 images total were used in this experiment; 57% (513) of them were used for training and 35% (315) for testing. From 8% (72) of the training data, validation data were obtained.

B. CNN Resnet 50

ResNet is an abbreviation for Residual Network, as depicted in Figure 1. Deep convolutional neural networks have achieved superior improvement in the domain of image recognition and classification over the years [16]. Delving further into enhancing the accuracy of classification or recognition and completing more complex tasks has become a prevailing tendency. However, the process of training neural networks with a greater number of layers has proven challenging due to issues like the vanishing gradient problem and degradation problem. Residual learning aims to address both of these issues [17]. Residual neural networks (ResNet) solve these problems by including a "Residual block," which consists of a "skip connection" adding the output of the previous layer to layer ahead as shown in Fig. 1. Should x and $F(x)$ have different dimensions, x is multiplied by a linear projection W to balance the dimensions of the output layer and the short-cut connection [18].

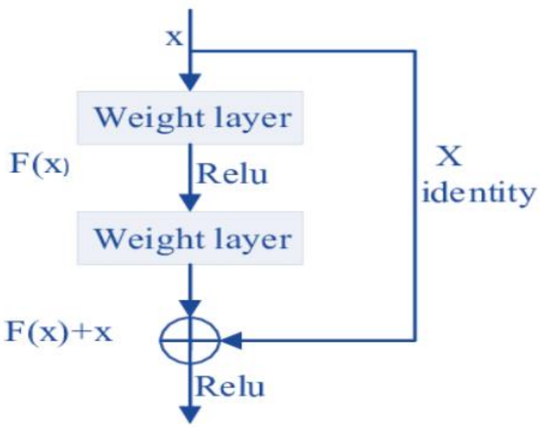

Fig. 1. Residual Network Building Block

Each layer in neural networks acquires low- or high-level features through task-specific training. In residual learning, the model seeks to learn residuals rather than attempting to learn features directly. The input "x" is incorporated as a residual to the output of the weight layers, followed by the activation process. The ResNet model makes advantage of Relu activations. ResNet 50 is a 50-layer residual network with several variants including ResNet 101 and ResNet 152. Medical image classification using ResNet as a pretrained model has produced good performance [17].

C. Inception MV4

Inception-v4 is a sophisticated convolutional neural network architecture that enhances earlier repeated cycles of the inception lineage. It accomplishes this by optimising the architecture, integrating a stem layer, and employing a higher quantity of inception modules than inception-v3. Overall, the architecture is rendered more uniform and simplified. Inception-mv4 is another neural network which is designed according to Inception-v4, Under the average pooling layer, this network comprised a single convolutional layer and two convolutional layers that were added in parallel [19].

IV. Experimental Results and Discussion

The experiment utilised the (LIDC-IDRI) Lung Imaging Database Consortium-Image Database Resource Initiative dataset, consisting of a total of 900 images. Of these, 57% (513) were allocated for training purposes, while 35% (315) were reserved for testing. A validation dataset was obtained from 8% (72) of the dataset. We have performed numerous experiments utilising the proposed CNN ResNet 50 technique, and the evaluation results demonstrated the efficacy of lung cancer detection. The results revealed have been compared with the Inception mv4 model. In order to train the ResNet 50 and Inception MV4 deep convolutional neural network models, used a learning rate of $1x10^{-3}$and employed the Stochastic Gradient Descent with Momentum (SGDM) optimization technique. Upon training the ResNet 50 Deep Convolutional Neural Network Model, it exhibited exceptional performance during the training phase, achieving a diagnostic accuracy of 100%, surpassing the Inception MV4 model. The following table provides a comprehensive breakdown of the results.

Table 1: Results of the ResNet 50 and Inception MV4 models

Model		**ResNet 50**			
Epoch	Iteration	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss
1	1	46.88%	26.43%	1.4899	1.6275
3	50	100.00%	99.35%	0.1253	0.1367
6	100	100.00%	99.84%	0.0281	0.0372
8	150	96.88%	99.84%	0.0585	0.0232
10	190	100.00%	100.00%	0.0097	0.0148
Model		**Inception MV4**			
Epoch	Iteration	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss
1	1	34.38%	18.76%	1.8538	1.4891
3	50	87.50%	80.42%	0.4762	0.5307
6	100	75.00%	84.83%	0.5368	0.4355
8	150	90.62%	92.66%	0.1479	0.2373
10	190	75.00%	94.62%	2.0655	0.1607

Looking at table 1 above, the experiment reveals that the ResNet 50 model consistently outperformed the Inception mv4 model across all evaluated metrics. At epoch 1, ResNet 50 achieved higher mini-batch and validation accuracies (46.88% and 26.43%) compared to Inception mv4 (34.38% and 18.76%), with a lower mini-batch loss despite a slightly higher validation loss. By epoch 3, ResNet 50 reached 100% mini-batch accuracy and 99.35% validation accuracy, significantly surpassing Inception mv4's 87.50% and 80.42%. This trend continued at epoch 6, where ResNet 50 maintained 100% mini-batch accuracy and nearly perfect validation accuracy (99.84%), while Inception mv4's mini-batch accuracy dropped to 75%, and its validation accuracy was 84.83%. At epoch 8, ResNet 50's performance remained high, with 96.88% mini-batch accuracy and 99.84% validation accuracy, in contrast to Inception mv4's improved but lower 90.62% and 92.66%, respectively. Finally, at epoch 10, ResNet 50 achieved perfect accuracy in both mini-batch and validation (100%), with minimal losses, whereas Inception mv4 displayed a decline in mini-batch accuracy (75%) and had higher mini-batch loss, though its validation accuracy was relatively high at 94.62%. Overall, ResNet 50 demonstrated superior diagnostic efficiency and accuracy in lung cancer identification compared to Inception mv4.

V. CONCLUSION

The objective of this paper was to illustrate the accuracy and efficacy of lung cancer diagnosis. using CNN ResNet 50 trained on LIDC-IDRI dataset. Deep learning techniques show encouraging results; thus, this work used the LIDC-IDRI dataset to identify lung cancer. The most recent studies on deep learning methods to detect or identify and diagnose lung cancer were examined in this work. The experimental result of the ResNet 50 model for the detection of lung cancer using the LIDC-IDRI dataset demonstrated that the ResNet 50 model performed significantly better across all of the metrics that were evaluated. ResNet 50 consistently achieved higher mini-batch and validation accuracies, reaching perfect diagnostic accuracy by epoch 10, and maintaining minimal loss values throughout the training and validation phases. This was accomplished with minimal loss values. These findings demonstrate that the ResNet 50 model is both effective and efficient in detecting lung cancer. As a result, the ResNet 50 model is a more trustworthy option for this application when compared to the Inception mv4 model.

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