

Lung Cancer Detection Using Xception Model

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Abstract: Lung cancer is by far the leading cause of cancer-related fatalities in both men and women worldwide. According to data from the WCRF, of the 2.09 million persons who received a cancer diagnosis in 2018, 1.76 million passed away (Worldwide Cancer Research Fund). Early sickness detection raises the chance of survival. Numerous computer-aided diagnostic techniques have been suggested and created to improve the survival rate due to the complexity of the issue. Convolutional neural network designs are suggested in this paper because of deep learning's excellent performance in difficult photo categorization issues. When a deep learning technique based on the combination of Xception was implemented, a model that generated 0.16 percent loss and about 64 percent accuracy was discovered. With the use of this model, Lung cancer patients will automatically be diagnosed. The model first utilises the Xception network to extract the deep features from the data, then passes the extracted features to be detected, before choosing the most crucial characteristics... Second, the typical cross-entropy loss is unable to better balance the mismatch across categories in the training set samples. Therefore, this research fuses the correlation between the two loss functions, Pearson's feature selection concepts, and optimises the issue. The model's findings are thoroughly contrasted and examined with those of other research in the literature. The Xception model employed in this experiment can help doctors more effectively diagnose and treat patients with lung cancer and can quickly and accurately identify youngsters. can better receive prompt medical care. Even if this model can't totally replace manual classification, it can nonetheless lighten the load on medical professionals, increase safety and dependability, and classify lung cancer with more accuracy.

Keywords: Lung Cancer, Xception Model, Diagnosis, Machine learning

I. INTRODUCTION

Lung cancer is by far the leading cause of cancer-related fatalities in both men and women worldwide. According to data from the WCRF (Worldwide Cancer Research Fund), 1.76 million persons died because of cancer in 2018, out of the 2.09 million people who received a

cancer diagnosis (21.7% of all cancer diagnoses) [1]. Around 80% of people survive cancer, even though the likelihood of survival rises with an early diagnosis [2]. The end outcome is the poor survival rate. Radiologists must be able to identify an aberration and characterise it as being symptomatic of a certain illness to identify possibly malignant lung nodules. Although diagnosis is challenging, pulmonary radiologists have high levels of diagnostic accuracy. According to a research, radiologists had an accuracy rate of 0.79 percent when it came to identifying lung cancer using CT images. However, there are still issues with disease diagnosis. The identification of changes in pre-existing interstitial lung disease, the diagnosis of moderate interstitial lung disease, and the miss rate for tiny pulmonary nodules are a few of these issues. Even with extensive clinical training and competence, many issues are challenging to resolve.

CADx (Computer-Aided Diagnosis) systems have long assisted radiologists in making early diagnoses and extending care services in a more prompt, effective, and accurate manner. In the past, CADx systems have used sophisticated image processing and segmentation techniques to distinguish between tumours and other diseases of a similar kind. As a result, the extraction of low-level features is an intricate and difficult procedure. However, recent research has shown that deep learning methods (an artificial intelligence subset) may be used to recognise and categorise cancer [4, 5, 6]. Due to the nature of these methods, it has proven effective in categorising various cancer kinds and extracting low-level to high-level characteristics from a variety of datasets [7].

This paper investigated the Xception model. The most advanced approaches for automatic feature extraction and automatic recognition, including machine learning and deep learning methods, were taken into consideration.

A. Lung Cancer

The most common kind of cancer, adenocarcinoma, is discussed. First, cancer is a mass of abnormal cells that grows and spreads until it invades surrounding tissues. These cells may multiply almost everywhere in the body. The human body has tens of trillions of cells. To survive and pass on their genes, these cells split into new cells. When a result, as cells get older, they die and are replaced

by younger ones. Cancer cells do, however, go through this stage of cell reproduction. They are abnormal because those cells' genes include errors or mutations. This is how tumours develop: the old abnormal cells survive when they should have died, and the new ones grow even though they are not needed.

Tumours can be either benign or malignant. The difference between the two is that malignant tumours spread via nearby tissue, whereas cancer spreads through the blood or lymphatic system to distant organs and damages nearby tissue or organs. On the other hand, benign tumours do not invade nearby organs or tissues. Once removed, they offer minimal harm to the patient, despite the fact that they can get quite big (unless the tumour is in the brain) [8].

In the chest are two cone-shaped breathing organs known as lungs. The primary jobs of the lungs are to expel carbon dioxide and carry oxygen into the body. The definition of lung cancer is the rapid multiplication of abnormal cells in one's. Similar to healthy cells, these cells do not provide any particular function. Instead, they develop into a tumour and prevent the lung from carrying out its vital role as a part of the respiratory system. According to the size of the cell where the illness first manifests, there are two types of lung cancer: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC) (NSCLC).

The most common kind of lung cancer, known as adenocarcinoma, starts in the glandular cells on the outer region of the lung. Squamous cells, which are flat, thin cells, may also be where NSCLC starts. These cells line the bronchi, which are the wide airways that branch out from the windpipe, as seen in the picture below.

This specific type of cancer is known as lung squamous cell carcinoma. Large cell carcinoma is yet another non-small cell lung cancer kind, however it is less common. There are also a number of unusual subtypes of non-small cell lung cancer. Examples of these are sarcomatous cancer and sarcoma. [9]

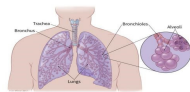


Figure 1 non-small lung cancer - Adenocarcinoma

The middle layer of lung cells is where SCLC typically starts. The two main kinds of small cell lung cancer are small cell carcinoma and combination small cell carcinoma (mixed tumour with squamous or glandular cells, respectively) [9].

Both types of cancer are more likely to develop lung cancer as a result of smoking (including cigars, tobacco, pipes, both past, and present). According to all studies and official sources, smoking is the main risk factor for this illness. The longer the smoking history, the earlier one starts smoking, and the more often one smokes, the higher the risk. Asbestos, arsenic, chromium, beryllium, nickel, soot, tar, radiation, living in a location with poor air

quality, having a family history of lung cancer, harbouring the HIV virus, and many more are additional risk factors. [10].

B. Xception Model

As the name indicates, transfer learning entails transferring the parameters of the learned model (pre-training model) to the new model to aid in the training of the new model. In the medical profession, we frequently require a huge number of photos for analysis and diagnosis. In order to train a deep CNN [8] model, like as ResNet, Xception, or Vgg, we also need a big number of datasets because they include millions of trainable Parameters. Learn the Xception model first before learning about the model's application. In this article, Xception is combined with various CNN structures to accomplish. Compared.

Dr. Laurent Sifre was the first to put out the idea of Depth wise Separable Convolution in writing [9]. In 2014, the Google team claimed that Google Net outperformed the conventional convolutional layer. The so-called Inception structure allows for the employment of convolution kernels of various sizes inside a single layer. CNN has made a tiny breakthrough thanks to this invention. Improvements to Inception V2 [10], Inception V3 [14], and Inception V4 [12] have since been suggested. First off, the typical structure in Inception V2 frequently takes the shape of a 5 5 big convolution kernel. However, the V2 structure uses two 3 3 convolutions to somewhat improve the depth of the network.

II. LITERATURE REVIEW

. Ganeshan et al. [2] made the discovery that textural traits might be utilised to differentiate between malignant and benign nodules, stage cancer, and control glucose metabolism in 2010. The study involved 17 participants with non-contrast enhanced CT images. The Laplacian of Gaussian filter was used to the CT scans to provide filtered pictures in four different sizes: coarse, fine, medium, and unfiltered. The properties of mean grey level intensity, entropy, and homogeneity were produced for each of these filtered zones.

In 2013, Krewer et al. [3] analysed lung nodules using texture and shape criteria. The classification of malignant and benign nodules was accomplished using a variety of classifiers, including nearest neighbours, decision trees, SVM, etc. Using the nearest neighbour classifier and textural properties, they found that the highest classification accuracy was 90.91 percent. They also found that texture characteristics, such as wavelet and laws features, received higher scores during the feature selection process. This serves as an example of how textural traits might be utilised to forecast outcomes for the classification of lung nodules.

III. METHODOLOGY

In the realm of medical imaging, convolutional neural networks (CNNs) have lately risen to the top of the most popular technologies list. The bulk of deep learning

applications for cancer diagnosis are built on CNNs. Convolutional neural networks, a type of deep learning method, take an image as input, give each object or aspect in the image a value (learnable weights and biases), and then are able to distinguish between them. In comparison to the CNN algorithm, other classification techniques require more "pre-processing." Even though the CNN could pick up these filters/specifications with enough practise, filters are often built manually [6]... The CNN structure is based on the "visual cortex" of the brain and resembles the interconnected configuration of "neurons" in the human brain. Each neuron only uses a limited area of the visual field, called the "Receptive Field," to respond to inputs. Together, these fields span the whole visual field. In this study, convolutional neural networks were used to investigate lung cancer. To determine if this condition was cancerous or not, we used deep neural networks built on the MATLAB platform. The recommended approach is graphically depicted in Figure 1.

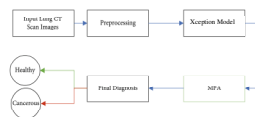


Figure 2 Graphical representation of the proposed method

A. Xception Architecture

One of the most well-known and robust convolutional neural networks is the Xception architecture, which is developed under many key ideas, including convolutional layer, depth-wise separable convolution layer, residual connections, and inception module [1]. Additionally, CNN's architecture has been utilised to build the conventional activation function [6] and is crucial for the activation function. In this work, the activation function of the Xception model has been suggested for enhancing the accuracy of the first diagnosis of lung cancer [5].

According to the description of the Xception theory, which is based on the Inception module, cross-channel correlations and spatial linkages inside CNN feature maps are produced and are completely dissociated [7]. The overall module of an Inception v3 is seen in Figure 1.

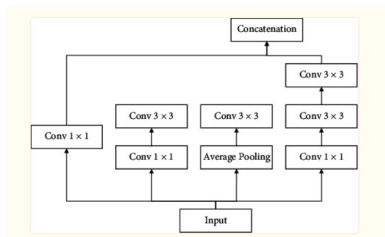


Figure 3. Overall model of inception v3

As seen in Figure 3.2, the model is built on cross-channel correlations created by the input data being divided into four groups before being convolutional with a size of 1 1, average pooling, and mapping correlations created with a size of 3 3, and lastly forwarded to the concatenation

layer. Figure 3.3 displays the overall module of the examined Xception module.

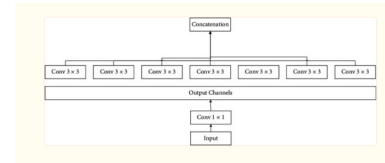


Figure 4 Overall exception model

B. Pre-processing Step

The first step in the recommended approach is pre-processing the input data to remove any occurrences that could have adverse effects on the CNN. After being trained and injected into a CNN with a specific architecture, the pre-processed images are evaluated using the image data. The lung image collection has to have some lights and disturbances eliminated, even with the greatest imaging. These disruptions may potentially affect the accuracy of the final classifier. A low-pass filter can be added to reduce the detrimental impact of high-frequency pixels on the photographs.

1. Noise Removal

As was already said, reducing noise from the input images is crucial for medical imaging. It is recommended to keep the image crisp while ignoring the image's edges when utilising the noise reduction step. Popular low-pass filters, such as median filtering, determine each output pixel based on the input pixels' average brightness values for the pixels around it [7]. The median size of a pixel's surrounding pixels determines its size in median filtering. Since the centre filter is less sensitive to throw values, it may eliminate these areas without affecting the image quality. Additionally, this filter maintains the positioning and contour of the edges while minimising variations in light intensity [8]. This filter by m n neighbourhood sorts in ascending order by choosing the sorted values and swapping them out with the centre pixels. The median filter also quickly eliminates the salt and pepper noises [9]. Therefore, we pre-processed the input photographs in our research using this filter. In median filtering, the median value of a pixel's neighbours is used to replace it.,

$$y'_{(m,n)} = \text{median} (x_{i,j} : (i, j) \in \tau),$$

when the neighbourhood neighbours are described (m, n). Figure 2 displays a straightforward example of using median filtering to the noise reduction of lung pictures. It should be noticed that in this case, the filter size is 5 5.

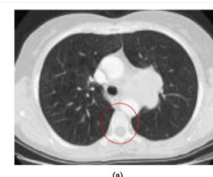


Figure 5 Small filtering of the CT scan image.

2. *Image Level Balancing*

After the noise has been eliminated, normalisation is required to scale the recorded images between 0 and 1 to lessen the dataset's complexity. We applied the min-max method to standardise the data. The current study normalises on a scale of 250–250 for this problem. The following definition of a normalised picture is predicated on the use of a dimensioned grayscale image and the constraint indicated above...:

$$I^* = a_{new} + \frac{b_{new} - a_{new}}{b - a} \times (I - a),$$

C. *Convolutional Neural Network*

For processing in the research's architectural design, certain images of the same scale are needed. Therefore, all the images were downscaled to 227 227 before CNN trained them. Figure 3 shows how this approach is simply applied to the database under discussion.



Figure 6 Database example illustration

Network training really minimises the error function between the network's actual and predicted outputs. The network's free parameters, or its weights and biases, are improved to achieve this [11]. In this study, supervision served as the primary method of instruction. In this method, a supervisor manages the network's training behaviour and instructs it on how to learn effectively. In other words, examples of inputs and outputs are displayed to the network [12]. The amount of the erroneous value is then determined by comparing the network's output to the desired output.

The biases and weights are then selected to lower this value. Either sequentially after applying each training sample, known as "sequential," or batch-wise after applying all of the training data, known as "batch," can be used to train the network parameters.

The first method requires less memory but is less stable since each training sample may change the network settings. Even though the second method uses more RAM to hold the settings, it will be more stable. Therefore, we used the batch mode in the following. We use batches of size 32 to train the database images for this inquiry. Three "convolutional" layers and three "max pooling" levels make up the architecture of the deep neural network. The overall architecture is seen in Figure 4...

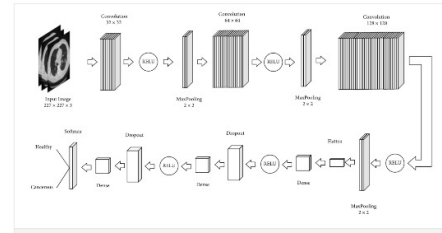


Figure 7 Total architecture

The convolutional layer contains the core CNN kernel, and the output mass might be a 3D mass of neurons. The mathematical method known as convolution is utilised in signal processing to apply convolutional procedures to the inputs from the neurons. The recommended model makes use of the three layers of 32 32, 64 64, and 128 128 since their filter size is the most important convolutional layer parameter. After the convolutional layer, a pooling layer has been employed to reduce the special size (depth).These speeds up the network and reduces the number of parameters. The pooling layers reduce the number of output layers in the filter. In this experiment, a 2 x 2 filter was used.

The key idea is to subsample the input image in order to save memory, reduce complexity costs, and reduce the number of network parameters.

The size decrease of the input picture also reduces the neural network's sensitivity. Like in the convolutional layer, each neuron in the pooling layer is connected to some neurons' output. To reduce the size and speed up the calculation, a pooling layer is employed for sampling. In this investigation, the image is subjected to the pooling layer with a 2 2 window. From the four pixels already existing in this window, the largest one is picked and transported to the next layer. Figure 5 shows the maximum pooling method.

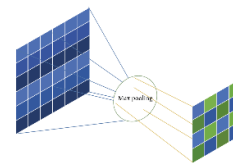


Figure 8 Max pooling

In order to introduce nonlinear operations into a system that has fully computed the linear operations in the computational layers, an activation layer is applied after each convolutional layer [13]. Because of their excellent computational efficiency and ability to train networks more rapidly without sacrificing accuracy, RELU layers are utilised in this study to achieve this objective. The performance profile of the RELU activation function is shown in Figure 6. All the input images are sent via the RELU layer's function, which converts all of the negative activations to zeros. By using this layer, the model and network's nonlinear properties were improved without harming the convolutional layers...

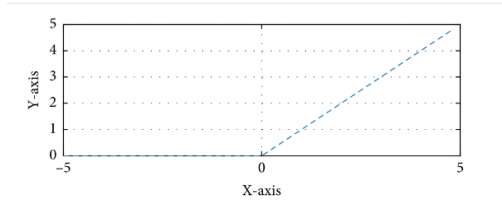


Figure 9 Dropout

Due to the "dropout" layer being taken into consideration during training based on a known probability, certain neurons' output has dropped. As a result, another network becomes accessible, and when this network is given independent of other neurons, it may locate and make use of strong characteristics. Thus, employing the dropout strategy avoids the overfitting problem [14]. A fully connected deep network includes a high number of parameters, which makes training time-consuming and increases the possibility of premature convergence. Therefore, among the fully connected layers, the dropout layer has been used to reduce the parameter. Figure 7 illustrates the process for adding the dropout layer.

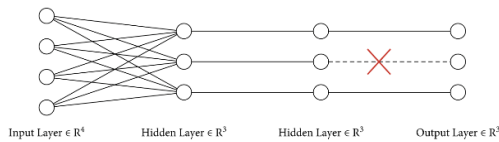


Figure 10 Dropout layers

The convolutional and pooling layers will have produced a significant amount of small-sized feature data. When these layers are coupled to a Softmax classifier, the input picture markings are known, therefore the network may be trained to recognise all pictures by feeding it all of the learned images and their markings. Specifically, during training, the system looks for the filter weights and layer coefficients that will produce the classification with the least amount of error. The output "Flatten" layer, the convolutional layers, which are multidimensional tensors converted to 1D tensors, and finally the "Optimizer RMSprop," which is utilised for evaluating numerous factors, have all been included in the weight's optimization. The leftover images from the data that weren't utilised for training are used to test the network. In this instance, the output of the layers is used as the necessary image feature vector. The deep neural network compares the image feature vector with the feature matrix at the conclusion in order to understand some aspects of the data. However, in order to categorise the data, we need a set of probabilities to make the ultimate decision [15]. A common function for normalising the probability values in a standard range is called SoftMax (0 to 1).

As noted, the "Optimizer RMSprop" approach has been used to determine the weights in the best possible way. The system's optimization process is based on reducing cross-entropy [16], which may be expressed mathematically as follows.

$$L = \sum_{j=1}^M -d_j \log z_j \tag{3}$$

where N defines the samples number, $d_j = (0, \dots, 0, \underbrace{1, \dots, 1}_k, 0, \dots, 0)$ signifies the desired output vector, and z_j represents the obtained output vector of the m^{th} class which is formulated below:

$$(z_j)^0 = \frac{e^{d_j}}{\sum_{k=1}^M e^{d_k}} \tag{4}$$

Equation (3) can be extended by considering a weight penalty as η as follows:

$$L = \sum_{j=1}^M -d_j \log z_j + \frac{1}{2} \eta \sum_{k=1}^K \omega_{k,p}^2 \tag{5}$$

where denotes the total number of layers, defines the layer connections, and specifies the weight of the connections.

There are several study papers available for the best CNN structure [17]. We are now creating a revolutionary metaheuristic-based optimal strategy because of this.

In this study, we first choose the algorithm's minimal (min) and maximum (max) restrictions to avoid system errors. For instance, max determines the size of the sliding window, while min is set to 2 as the least number that is permitted for max pooling. It should be noticed that the input data value must be greater than the sliding window value. The CNN's hyperparameters are set to 10 integer values, with 100 being the initial population. The answers are then assessed. The cost function in this study was the optimised CNN's half-value accuracy. The backpropagation technique must train all of the population members on the lung cancer dataset, which results in a significant computational cost for the whole methodology. The following two traits are considered for optimization in this study:

$$W = \{w_1, w_2, \dots, w_p\},$$

$$A = \{a_1, a_2, \dots, a_A\},$$

$$w_n = \{w_{1n}, w_{2n}, \dots, w_{Ln}\},$$

$$b_n = \{b_{1n}, b_{2n}, \dots, b_{Ln}\}, \quad l = 1, 2, \dots, Ln = 1, 2, \dots, A,$$

where l stands for the layer index, represents the group of agents, specifies the lean mass in the zone, and, in the other direction, and represent the total number of concealed layers and agents. The CNN's error cost function is shown as follows:

$$E = \frac{1}{T} \sum_{i=1}^T \sum_{j=1}^k (d_{ji} - o_{ji})^2,$$

where indicates the number of trainings samples, represents the number of output layers, and represents the aim and expected output of the CNN. The local optimum that the ensemble techniques could resolve rapidly captured this strategy. Additionally, the backward phase, which has a high computational cost, is not necessary with metaheuristics. The next part goes into more depth about how the marine predator's algorithm was used in this study.

D. Xception

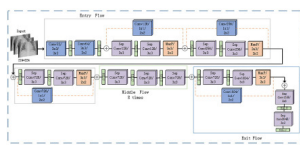
Convolutional neural networks (CNNs) for image identification are multi-layer neural networks made up of

convolutional layers for feature extraction and sub-sampling layers for feature processing. They play a crucial role in the field of computer vision [45]. This work uses the CNN-based Xception backbone model, which is an efficient way to gather information about the properties of lung cancer images. However, they are unable to handle sequential data because of a lack of specific performance in the learning dependency of cross-sequence information.

In this study, we present a model incorporating Xception network to better extract lung cancer picture attributes for the experiment, as shown in Fig 4. The network's batch size, picture quality improvement, and other parameters are then fine-tuned using the training image dataset to increase the model's accuracy and generalizability.

Finally, the features produced by the two Xception models are combined and analysed using the neural network attention mechanism. The features are then normalised and serially fused into fusion features using the fully connected layer FC. [4].

It is possible to better combine cross-channel correlation, spatial correlation mapping, and feature extraction from the Xception model. At the same time, the design consists of 36 convolutional layers that can be broken down into 14 modules. The output block, intermediate block, and entry flow are the three main divisions of the architecture. All of these modules, with the exception of the first and last modules, contain linear residual connections that are entirely based on the convolutional neural network architecture of the highly separable convolutional layer [15], which serves as the foundation for the network's feature extraction. An input picture with the dimensions 224 224 3 is obtained and delivered to the input block in the first section of the Xceptionnetwork. It is eventually produced by the input block following an intermediary block that goes through eight repetitions. Create three-dimensional data from four-dimensional lung cancer feature output so that it may be read by the following layer and sent to the second half of the model architecture. Four layers of dense wiring completely link the output data, and the first three layers' number of neurons drop at a pace of two times every layer. Using the weight matrix and the RELU activation function, the preceding local features are put back together into a full graph. Predictive categorization is carried out in the last layer by using the sigmoid activation function.



IV. SYSTEM IMPLEMENTATION

The lung cancer dataset was obtained over a three-month period in autumn 2019 in the specialised institutions for the Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD). It includes CT scans of lung cancer patients in various stages of the illness as

well as healthy volunteers. Oncologists and radiologists remarked on IQ-OTH/NCCD slides at the two centres. 1190 pictures representing slices of 110 instances' CT scans are included in the collection (see Figure 1). Figure 1 shows. There are three classifications for these occurrences: benign, malignant, and normal. Of these, it has been found that 40 of the cases are malignant, 15 are benign, and 55 are normal cases. Each CT scan was first compiled in DICOM format and contains several slices. Each of these slices, which range in size from 80 to 200, shows an image of the human chest from different sides and perspectives. Gender, age, educational attainment, place of residence, and manner of life are all different in the 110 examples. They include individuals who work for the Iraqi ministries of oil and transportation in addition to farmers and gainers. The bulk of them are from the provinces of Baghdad, Wasit, Diyala, Salahuddin, and Babylon, which are in the heart of Iraq. The dataset may be obtained online at on Kaggle (30).

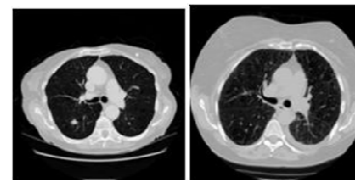


Figure 11 Two snapshots of lung screening (Left – Cancer; Right – No Cancer)

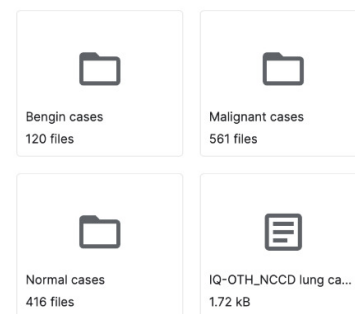


Figure 11 Snapshot of the repository folders

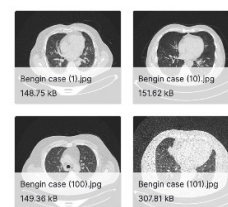


Figure 12 Database with Benign cases

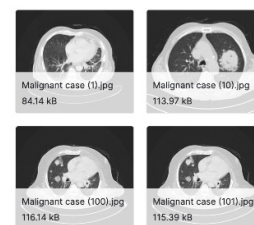


Figure 13 Database with the malignant cases

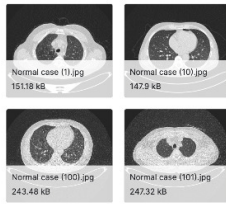


Figure 14 Database with normal cases

As seen above, the algorithm's input data. There is a nodule that has been labelled as malignant on the left side of the CT scan. The input on the right is marked as "non-malignant," and there are no nodules in the lung area.

A. *Transfer Learning*

I used transfer learning since the small quantity of data drastically limits the algorithm's ability to learn to generalise the current challenge. This method makes use of a model that has been trained on a sizable dataset (in our case, the ILSVRC dataset) [5] and applies the new learning to a different computer vision problem. The core tenet of transfer learning is that you may use knowledge that the model has already learned to spot patterns across a variety of images and solve new problems [6]. This approach is particularly advantageous for limited datasets when compared to starting with a randomly initialised model [7].

Furthermore, transfer learning is exclusively performed by retraining the linear layers of the convolutional models, commonly known as the head. The convolutional layers—which extract features and analyse the images—retain the same pre-learned weights from ImageNet and are only trained and initialised randomly as a result. The strategy used in this work is separated into two phases: the first involves keeping the convolutional layers' initial weights and simply training the head; the second involves unfreezing the convolutional layers and progressively training them by changing the model's learning rate.

B. *Why Python*

The flourishing machine learning community now uses it as an unwritten standard.

Artificial intelligence algorithms are developed using Python to solve complex problems. The graph below displays Python's growth over the previous five years in the field of machine learning.

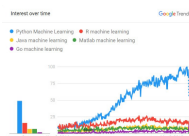


Figure 16 The growth of the five most common machine learning programming languages over the last five years

Python serves several purposes for me. To begin with, using Python is easy. Most people are drawn to it due of its straightforward and approachable syntax. The bulk of

ML developers pick Python because of the vast array of modules and frameworks that may be used for a variety of problems. Some helpful libraries for the artificial intelligence community in particular Beginners may easily understand machine learning and deep learning techniques thanks to a high-level software library called Fastai. Numerous machine learning-related classification, clustering, and regression techniques may be found in the software package known as Scikit-learn. An open-source library called Keras is useful for testing deep neural networks.

Additionally, Python has a solid corporate and community foundation because to its market presence extending back to 1990. Both the community and machine learning engineers gain from new engineers being able to swiftly enhance their knowledge of the field. Last but not least, because it allows cross-platform and cross-language operations, Python is very portable and extensible. Python has shown to be relatively straightforward and well-suited for such tasks; as we previously mentioned, GPUs played a significant influence in the overall development of these algorithms.

In this section, we'll discuss the performance of the classifiers we created for the lung cancer problem. The training phase utilised 400 total photographs, of which 75% were used to generate the training set.

V. RESULTS

```

...
def __init__(self):
    self.model = models.vgg16(pretrained=True)

    self.model.classifier[5] = nn.Linear(4096, 1000)
    self.model.classifier[6] = nn.Linear(1000, 1000)

    self.optimizer = optim.Adam(self.model.parameters())

    self.device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
    self.model = self.model.to(self.device)

    self.train_loader = Data_loader(train_data_loader_args)
    self.val_loader = Data_loader(val_data_loader_args)

    self.loss = nn.CrossEntropyLoss()

    self.train()

...

```



Figure 5. 1 Training and testing Accuracy

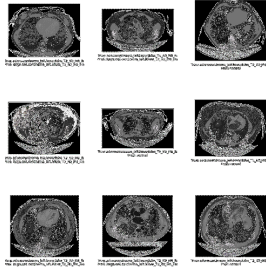


Figure 5. 1 Dataset Example

Confusion matrix:

[[59 38 16 7]

[17 13 17 4]

[26 16 7 5]

[26 31 25 8]]

(0) adenocarcinoma left. lower. lobe_T2_N0_M0_Ib

(1) large. cell.carcinoma_left.hilum_T2_N2_M0_IIIa

(2) normal

(3)squamous.cell.carcinoma_left.hilum_T1_N2_M0_IIIa

VI. CONCLUSION

. It often takes several samples to build deep learning networks to detect lung cancer. It is challenging to get many samples since medical samples are rare and valuable. The goal of this study was to research and test a new data enhancement technique in conjunction with a - Xception network to boost the performance of lung cancer identification: In order to address the issues of uneven sample classification and inadequate samples, the first step is to expand the samples using the CNN with conditions and five data augmentation techniques including flipping, rotating, and adding Gaussian noise. Next, an Xception network is created to identify the cancerous cells. This network uses an adaptive dual-channel feature extraction module to gather information about the target's surroundings, and a convolutional attention module to help the network learn features more precisely. 52 lung nodules are used to test the network after it has been trained and verified using 274 data set pictures (154 benign and 120 malignant) (23 benign and 29 malignant). According to the trials, the network has an accuracy of 63.46% and an AUC of 0.929: This study reveals that the performance of the Xception network in classifying lung nodules is superior to that of the traditional classification networks and pre-trained networks.

This will be made increasingly clearer with the use of additional clinical data. Extra demographic data aids in developing additional awareness-raising strategies in more vulnerable areas. Ordinarily, lifestyle variables including dietary choices, cultural practises, and social interactions have a significant impact on many diseases and adding up these effects will be quite helpful in decision-making.

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