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Lung carcinoma prediction for computed tomography using deep learning

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Abstract
Lung carcinoma is one of the most common diseases in the world. In India one of the most occurring disease is lung cancer and lot of people die due to the reason that it can only be cured during its initial stages. It is caused by the uncontrollable cell proliferation in lung tissues. It can be treated in Initial phase by seeking therapy is recommended. Only Computed Tomography (CT) scans and blood test results can detect this. The tumour is diagnosed by blood test after the humans have been affected for at least four years. As a result, CT scanning is utilised to determine the early stage of cancer. CT pictures are classed as normal or abnormal. Focusing on the tumour region reveals the aberrant image. The dataset is in jpg format and is made up of CT scans. The dataset is in jpg format and is made up of CT scans. This algorithm is used to process images. During training, image expansion method like zooming, linear fills, trimming, and rotation are used to sample, to improve classification success rates. Cancerous cells are discovered early by whenever the lungs provide oxygen to humans and expel carbon dioxide from the body as it plays a key role. Using various deep learning models, we can detect lung cancer. These deep learning models are employed across a wide range of datasets. We can achieve accurate findings by employing the image processing method. Because the AlexNet model was so successful, the model-derived characteristics are final used to fully connected layer, individually as feedback to the softmax layer. Both together yielded an accuracy of 99.52%.

Keywords: Lung carcinoma, computed tomography, AlexNet, softmax layer

Introduction
In the medical industry, the study and evaluation of a lung CT picture is a time-consuming and highly qualified process. The subjective examination produces diversity among the observers. Computer-based systems are in high demand for these reasons. Existing technology can be used to perform the diagnostic process. As a result, the cost will be significantly lowered. Deep learning is one of the most commonly used models for lung cancer diagnosis. Convolutional Neural Network (CNN) models were used. The Alexnet model is utilized to forecast lung cancer. It is made up of eight layers. Five of the layers are convolutional and maxpooling. Three of them are completely connected layers. We employed a hybrid model in which the CNN Alexnet model is linked to a machine learning classifier dubbed the softmax layer. The last layer is the softmax layer. The CT image dataset in our study is divided into two categories: cancer and non-cancer.

Literature Review
CNN algorithm is a component of deep neural networks that was utilised for feature extraction and classification. AlexNet is a CNN model with eight layers, the final of which is coupled to the softmax layer. The 'Adam' is the optimizer technique used in this model. Identification of lung cancer utilising CT scans of the lungs and CNN with little duplication and optimum applicability. In this method a dataset is defined into two normal and malignant image datasets. Those images were trained and tested to predict the lung cancer.
Google Lens is the well-known application is used to find the image and text of the data whenever the user gives an input to the google lens. This takes the image as input and shows the related images as output. In this text data also used. Whenever an image of text data is given then, it selects the text part and gives us the copy option with search.
The studies were conducted using an available dataset of CT images. CNNs will extract features and classify them [1].

The most common kinds lung Carcinoma and categories are listed. Patients' data collected through web for online detections utilising the RF algorithm [2]. Noise is removed using the weighted mean histogram equalisation method. The IPCT is used to improve image quality [3]. By integrating a low-dose CT scan dataset with full-mode iterative recombination and a CNN-based deep feature extraction method, a probabilistic model is used to diagnose lung Carcinoma [4]. Tests are carried out on afflicted person CT pictures after one, two, and three years. Deep Learning identified 94 percentage of incident and interval lung Carcinoma within 1-3years of the subsequent CT monitoring examination in these each one deemed huge risk [5]. In this test, two classifiers based on supervised machine learning are used to classify CT images as normal, malignant, or benign. This stage's operation is governed by the standard backpropagation algorithm [6]. For pattern recognition, a novel model called SVM-CNN hybrid model is built by combining SVM with CNN. SVM was used to replace the last output layer of CNN in this case [7]. DCNN has 2 fully connected layers, 3 convolutional layers, and 3 pooling layers. To avoid overfitting during the training phase, each image is subjected to a series of operations such as reflection, rotation and filtering. It has a 71% success rate in the classification [8].

A backpropagation ANN has 133 Persons with anti-lung carcinoma. It guaranteed a 99.2% efficiency [9]. An image classifier dubbed computational histomorphometry was proposed in its early stage detection using pattern, orientation, and nuclear orientation from digitised tissue microarray. This model has an 81% accuracy [10]. Three stages are taken to extract the images from the edges. Finally, the vertical and horizontal directions of all transitions' edge maps were removed and concatenated [11].

Methodologies

Normal lung CT images

There were CT pictures of no lung cancer used in this study. The initial dataset included 50 photos, and image augmentation techniques such as zooming, linear fills, trimming, and rotation were applied. To avoid overfitting during the training phase, each image is subjected to a series of techniques such as reflection, rotation, and filtering. When a lung CT scan is run through this, it displays the CT image's outcome by predicting whether or not the person has lung cancer.

Lung cancer CT images

In this investigation, CT images of no lung cancer were used. Image augmentation techniques such as zooming, linear fills, trimming, and rotation were used on the initial dataset of 50 pictures. Each image is subjected to a range of techniques such as reflection, rotation, and filtering to avoid overfitting during the training phase. When a lung CT scan is run through this, it predicts whether or not the person has lung cancer based on the CT image.

Convoltional Neural Networks

Convolution compares images one by one. By comparing the image's position with the training image, the real trained image is compared to the input. CNN outperforms full picture matching techniques in terms of seeing similarly. It is made up of 3 layers: the ReLu, the maxpooling, and the completely connected layer. It is a component of deep neural networks that was employed in the feature extraction and classification process. It is divided into three models: AlexNet, VGG-16, and LeNet. This proposed algorithm made use of AlexNet. AlexNet's architecture is made up of three pooling layers, five convolutional layers, and 3 layers which are fully connected. The suggested model's last layer is linked to the soft-max layer. It is the probability function, with values ranging from 0 to 1. The value which is high to then it is true.

Problem Definiton and Formulation

To develop an efficient algorithm to classify medical images leveraging deep learning (DL). To calculate the effectiveness of various DL algorithms in predicting lung cancer in human. To develop a diagnostic model with appropriate user interface for cancer related diseases in human. A well-defined user interface was done for finding the lung carcinoma. In this the dataset is classified into normal lung and malignant lung. Normal lung means lung without cancer and malignant lung means lung with cancer. Image augmentation methods were done for the images. For the testing, the augmentation images are not applied because to prevent the overfitting. In this we used TensorFlow for the algorithm. We used many python libraries for the prediction. TensorFlow is an open source it has complex deep learning models such as convolutional neural networks. It consists of edges and nodes that perform all mathematical operations.

Data Gathering and Pre-processing

CNN are used to categorize and identify the images based on their similarity from the trained data set.

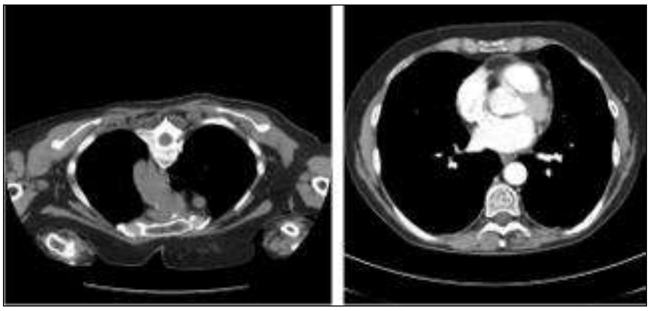

Fig 1: (i) Normal Lung CT image, (ii) Lung Cancer CT image

Gathering User Data

The dataset is compiled from a variety of sources, including general and hospitals. We acquired hundred photos, fifty of which were cancer images and 50 of which were normal photographs. Due of the limitations of Python's format support, the pattern is DCIOM and changed to jpeg pattern for training. The image has a resolution of 504 × 504 pixels. We are relying on information enhancement approaches to improve performance which will improve the categorization performance of CNN. The picture augmentation algorithms in this work are implemented in Python using the Keras package. Cutting, rotation, horizontal turning, width and height changes, and filling operations are performed on every object of the dataset. Alexnet is the oldest and most well-known picture classification database. This is CNN's most successful model. AlexNet's architecture is made up of 3 pooling, 5 convolutional and 3 layers of fully connected. To avoid overfitting, the test set was employed without any augmentation approaches.

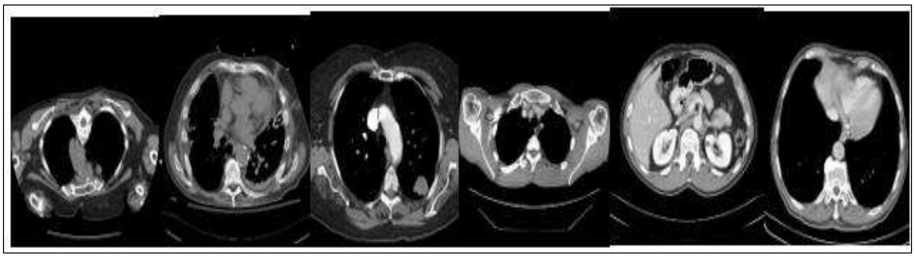

Fig 2: Original dataset

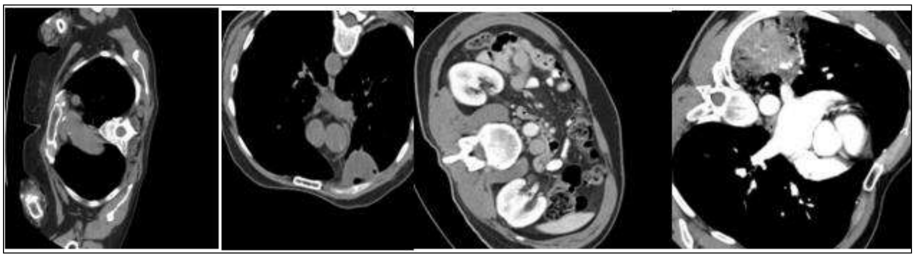

Fig 3: Augmentation techniques done for original dataset

In the fig 3. Shows the augmented images. Cutting, rotation, horizontal turning, width and height changes, and filling operations are utilised in this augmentation process for each image in the collection. To avoid overfitting, the test set was employed without any augmentation approaches.

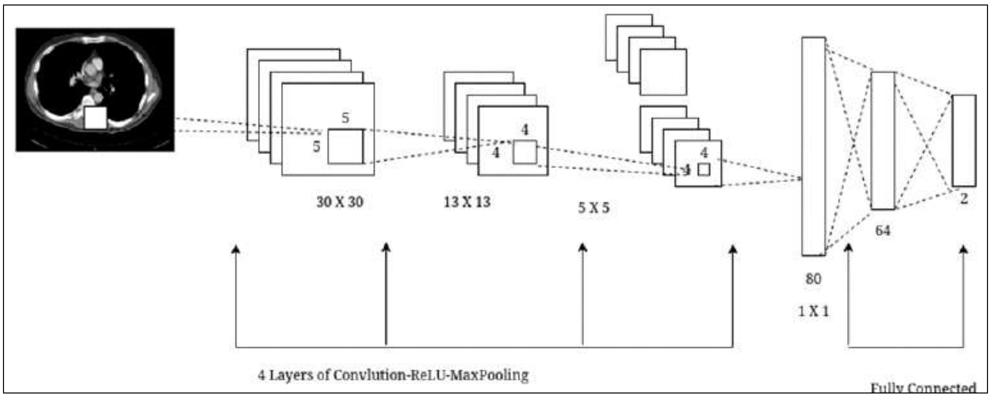

Fig 4: Architecture

Architecture

Figures 7.1 and 7.2 depict the architecture of the suggested model. It has eight layers in this architecture. The proposed approach was used to train an image dataset of the lungs. For the photographs, augmentation techniques such as linear fills, trimming, rotation, height and breadth alteration were employed. AlexNet, a CNN model, was used to train the images. The trained models are each trained independently. Prior to testing, the data should be collected independently. This produces the finest results while avoiding oversampling. The validation set is determined independently, and the subsequent probabilities are then assigned. This averages the data and forecasts the outcome.

Proposed Algorithm - Implementation

CNN is a subset of deep neural networks, was the algorithm we employed. It is mostly utilised in image and video recognition, medical disciplines such as organ pictures, and recommender systems. Our paper is based on medical imaging, such as lung cancer CT scans. A completely connected network is defined by multilayer perceptrons. Each layer's one neuron is linked to all neurons in the next layer. AlexNet is the most commonly utilised CNN model in the algorithm. Using image augmentation techniques, the dataset is transformed into the augmentation dataset. This suggested method has 90x90 input layers and 2 output layers in total.

AlexNet, LeNet, and VGG-16 are the most commonly used models in CNN. AlexNet was employed in this proposed model. AlexNet was created in 2012 by Alex Krizhevsky, Geoffrey Hinton, and llya Sutskever [13]. AlexNet's network architecture consists of eight levels. Convolutional and max-pooling 5 layers, while 3 layers are fully linked. As a non-saturating function, ReLu (Rectified Linear unit) is employed. In the suggested technique, the last activation function, SoftMax, is applied. Deep CNN models are used to classify lung cancer CT images. The last completely linked layer of the AlexNet does deep feature extraction. Softmax is the final layer utilised when feeding deep features to machine learning models.

We employed five convolutional and maxpooling layers in this proposed model. Maxpooling layers were added after the convolutional layers. We were assigned a stride of 2 in the maxpooling layer. 'ReLu' is function employed. Then images results into negative and positive images. If it comes under negative values, it will assign zero. The flatten layer comes after the dense layer. The 'Dense layer' is the last two layers in the proposed model. ReLu is the activation function in the first layer, having 64 filters. The proposed model's layer is linked to the 'Softmax layer'. The final layer receives two filters. The probability distribution function is represented by the Softmax layer. It has a value between 0 and 1. Whichever decimal has the highest decimal, the outcome is determined.

Experimentation and Results

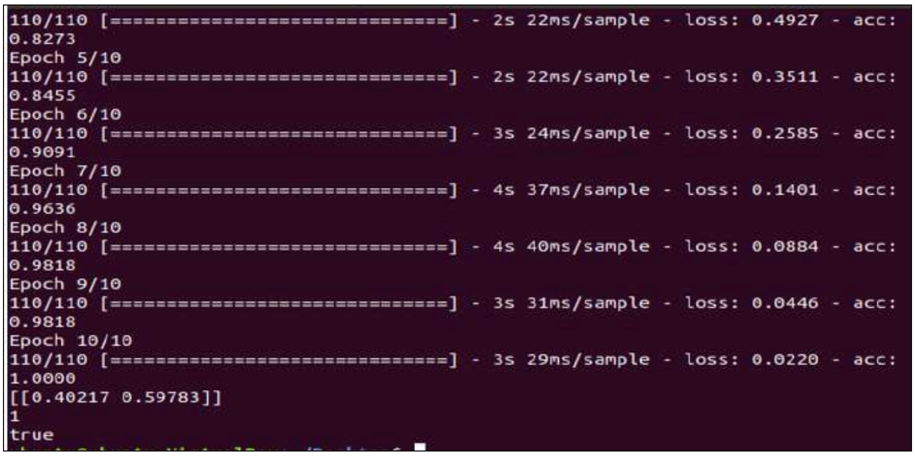

Fig 5: Output screenshot

Here is a screenshot of the lung cancer prediction output. The dataset is divided into two parts: true and false. If the lung has cancer, the result is 'true'; if it does not, the result is 'false'. To begin, we provide input to the programme in order to obtain output. We represented the output in three forms to display it. The first format shows a probability function with a value ranging from 0 to 1. Which of the following has the highest proportion of output? The second format is used to express binary values. It represents the output in 0 and 1 in this way. The values 0 and 1 signify 'false' and 'true,' respectively. It displays true or false in the final format. The last format is easily understood by the general population, regardless of whether he or she has lung cancer or not.

Conclusion and Future scope

To identify the patient whether having lung cancer or not, we designed a user interface (UI). In this, the user easily gets to know the details of the CT image. The user provides the input details of the user such as name, gender, age and lung CT image. The trained dataset checks the input such as image and shows the output. Whether he/she has lung cancer or not. By training the dataset of the lung computed tomography (CT) images, we are getting an accuracy of 99.52%. A hybrid model is used with different machine learning classifiers and CNN models to identify the lung cancer in humans. AlexNet is combined to the SoftMax layer to get the most efficient results.

To develop a well-defined User Interface where lab assistants can easily understand the ouput. By going through the deep research on lung cancer influential parameters, we are starting this work.

References

1. Mesut Toğaçar, Burhan Ergen, Zafer Cömert, Brain MR Net: Brain tumor detection using magnetic resonance images with a novel convolutional neural network model, Medical Hypotheses; c2020, 134.
2. Zhuo Liu, Chenhui Yao, Hang Yu, Taihua Wu. Deep reinforcement learning with its application for lung cancer detection in medical Internet of Things, Future Generation Computer Systems. 2019;97:1-9.
3. Mohamed Shakeel P, Burhanuddin MA, Mohamad Ishak Desa. Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks, Measurement; c2019, 145.
4. Reeja SR, Kavya NP. Real time video denoising, IEEE International Conference on Engineering Education: Innovative Practices and Future Trends (AICERA), Kottayam, India; c2012. p. 1-5. DOI: 10.1109/AICERA.2012.6306745.
5. Marjolein A Heuvelmans, Matthijs Oudkerk. Deep learning to stratify lung nodules on annual follow-up CT, The Lancet Digital Health. 2019;1(7):e324-e325.
6. Reeja SR, Kavya NP. Real time video denoising, IEEE International Conference on Engineering Education: Innovative Practices and Future Trends (AICERA), Kottayam, India. 2012, p. 1-5. DOI: 10.1109/AICERA.2012.6306745.
7. Reeja SR, Rino Cherian, Kiran Waghmare, Jothimani. Chapter 7 - EEG signal-based human emotion detection using an artificial neural network, Editor(s): Hemanth D. Jude, Handbook of Decision Support Systems for Neurological Disorders, Academic Press; c2021, p. 107-124.
8. Song QZ, Zhao L, Luo XK, Dou XC. Using deep learning for classification of lung nodules on computed tomography images. Journal of Health care Engg; c2017, 7.
9. Toney LK, Vessellw HJ. Neural networks for nodal staging of non-small cell lung Cancer with FDG PET and CT: importance of combining uptake values and sizes of nodes and primary tumor. Radiology. 2014;270:91-8.
10. Wang X, *et al*. Prediction of recurrence in early stage non-small cell lung cancer using computer extracted nuclear features from digital H&E images. Sci Rep. 2017;7:13543.
11. Reeja SR, Kavya NP. Noise Reduction in Video Sequences-The State of Art and the Technique for Motion Detection. International Journal of Computer Applications; c2012, 58(8).