# Lung Cancer Detection using Convolutional Neural Network

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**Abstract -** *Small cell lung cancer (SCLC) is a type of malignant tumour that is characterised by rapid growth and early metastasis spread. Early and accurate SCLC diagnosis is critical for improved survival. Accurate cancer segmentation assists doctors in better understanding the location and size of cancer and making better diagnostic decisions. In this project, we are using the YOLO framework to pinpoint the exact location of a lung tumour that is attached to the border of blood veins, as well as to classify the tumour. The R-CNN techniques demonstrated in Part 1 primarily use regions to localise objects within an image. The network does not examine the entire image, but only the portions of the image that are more likely to contain an object. The main advantage of using YOLO is that it is extremely fast and accurate.*

***Key Words:*** YOLO, Deep Learning, Lung Cancer, CNN.

## 1. INTRODUCTION

The lungs are shaped like a pair of sponge cones. The right lung has three lobes, while the left lung has two. The right lung is significantly larger than the left lung. The inhaling process delivers oxygen to the lungs. The lungs' tissue transports oxygen into the bloodstream. Lung cancer is a disease that causes abnormal cells to multiply and grow into tumours. Cancer cells in the blood can be conducted away from the lungs. Because the natural flow of lymph out of the lungs is toward the centre of the chest, lung cancer frequently spreads toward the centre of the chest. Lung cancer is classified into two types: small cell lung cancer and non-small cell lung cancer, which has three subtypes: carcinoma, aden carcinoma, and squalors cell carcinomas. Lung cancer was found to be the second leading cause of death in men and the sixth leading cause of death in women. Image processing has a wide range of applications in medical image processing for diagnosing lung cancer.

The proposed system description of lung cancer detection system includes four basic stages. The first stage begins with a collection of CT images (normal and abnormal) from the IMBA Home Database (VIA-ElCAP Public Access). The second stage employs several image enhancement techniques to achieve the highest level of quality and clarity. The third stage employs image partition algorithms, which play an important role in subsequent image processing stages, and the fourth stage obtains general features from enhanced partitioned images, which provide indicators of image normality or abnormality.

### 1.1 EXISTING SYSTEM

A trainable neural network that learns long-range 3D contextual information using a lightweight 3D convolution neural network and fine-grained intra-slice semantic information using a 2D convolution neural network. To deal with the anisotropic dimensions of CT volumes and reduce the computational cost of the 3D convolution neural network, they use spatiotemporalseparable3D (S3D) convolutions. We use dilated convolutions in a 2D convolution neural network to enlarge the receptive field while retaining high resolution to retain a large amount of semantic information about smaller objects. Create a hybrid features fusion module (HFFM) to effectively fuse 2D and 3D features. To address the issue of data imbalance training, they also use the generalised Dice loss function.

In a research paper, the scholars Researchers developed an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. The algorithm, CheXNet, is a l2l-layer convolutional neural network trained on ChestX-rayl4, currently the largest publicly available chest Xray dataset, containing over loo,ooo frontalview X-ray images with l4 diseases. Four practicing academic radiologists annotate a test set, on which they compare the performance of CheXNet to that of radiologists. We find that CheXNet exceeds average radiologist performance on the Fl metric. They extend CheXNet to detect all l4 diseases in ChestX-rayl4 and achieve state of the art results on all l4 diseases [1].

A deep learning framework for covidl9 screening from radiographs. The novel pandemic has spread all over the world in the last few months, according to arXiv preprint arXiv:2oo3.l4395, 2o2o Because of its ease of transmission, developing techniques to accurately and easily detect it and distinguish it from other types of flu and pneumonia is critical. According to recent research, the chest CT of patients suffering from shows certain abnormalities in radiography. However, those approaches are closed source and are not made available to the research community for replication and deeper understanding. The goal of this work is to create open-source and open-access datasets and to present an accurate CNN framework for machine learning. It's known as ResNet. This is accomplished by resizing input images progressively to l28xl28x3, 224x224x3, and 229x229x3 pixels and fine-tuning the network at each stage. Using this approach and automatic learning rate selection, we were able to achieve state-of-the-art accuracy of 96.23 percent (on all classes) on the dataset in only 4l epochs. This study presented a computationally efficient and highly accurate model for multi-class classification of three different infection types in addition to normal people. This model can help with early case screening and reduce the burden on healthcare systems [2].

A deep learning classifier framework for diagnosing covidl9 in x-ray images. arXiv preprint arXiv.org. Background and Goal: Coronaviruses are dangerous viruses that can cause SARS and Middle East Respiratory Syndrome (MERS-CoV). At the end of 2ol9, the novel 2ol9 Coronavirus disease was discovered as a novel disease pneumonia in the city of Wuhan, China. According to the World Health Organization's most recent reports, the world is experiencing a Coronavirus outbreak, with the number of infected people and deaths increasing rapidly every day (WHo). As a result, the purpose of this article is to introduce a new deep learning framework that will help radiologists automatically diagnose in X-ray images. Materials and Procedures: Due to a lack of publicly available datasets, the study is based on 50 chest X-ray images with 25 confirmed positive cases. There are seven different deep convolutional neural network architectures included, such as the modified Visual Geometry Group Network (VGGl9) and the second version of Google MobileNet. Each deep neural network model can analyse the normalised intensities of an X-ray image and classify the patient status as negative or positive. Experiments and evaluation of the have been completed successfully using 8o-2o percent of X-ray images for the model training and testing phases, respectively. The VGGl9 and Dense Convolutional Network models demonstrated good and comparable automated classification performance, with fl-scores of o.89 and o.9l for normal and, respectively. Conclusions: Based on the proposed framework, this study demonstrated the useful application of deep learning models to classify X-ray images. Clinical trials are the next step in this research [3].

Inverted residuals and linear bottlenecks in mobilenetv2. 2ol8 in the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. In this paper, we describe MobileNetV2, a new mobile architecture that improves the state-of-the-art performance of mobile models on multiple tasks and benchmarks, as well as across a range of model sizes. In addition, we describe efficient methods of applying these mobile models to object detection in a novel framework we call SSDlite. Furthermore, we show how to build mobile semantic partition models using MobileDeeplabv3, a reduced form of Deeplabv3 that is based on an inverted residual structure with shortcut connections between the thin bottleneck layers. As a source of non-linearity, the intermediate expansion layer filters features using lightweight convolutions. In order to maintain representational power, we also discovered that non-linearities in the narrow layers must be removed. We show how this improves performance and provide the inspiration for this design. Finally, our method decouples the input/output domains from the expressiveness of the transformation, providing a convenient framework for further investigation [4].

## 2. PROPOSED SYSTEM

The proposed system is based on the YOLO framework. Where we try to study and understand the existing vision module systems. Where we look into working of YOLO frameworks for the image acquisition system. Also, we try to build an Image classifier to find tumours and cancer in CT images. With that, we train a YOLO object detection to automatically detect Tumor and cancer with images via the dataset collected. Finally, Evaluate the results from the trained model.

Training and testing are two modules in our proposed system. The cropped CT scan image is input to the system in the Training module, followed by Pre-Processing to enhance the image. In the Testing module, the CT image is sent to the Pre-Processing phase, where it is divided into two parts to extract the lung region and the region of interest. The first two parts are feature extraction and selection, which are used to extract the tumour's main characteristics. The final component is the classifier, which determines whether the cancer was detected or not. We are using the YOLO algorithm and the YOLO framework to determine the exact location of the lung tumour and tumour attached to the border of blood vessels.

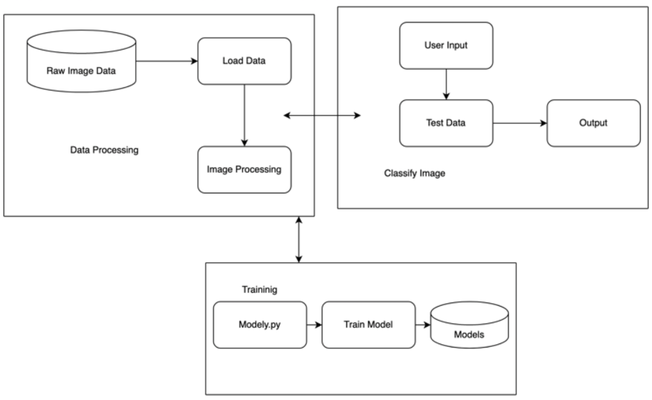



**Fig – 1** : Architecture of Proposed System

## 3. IMPLEMENTATION

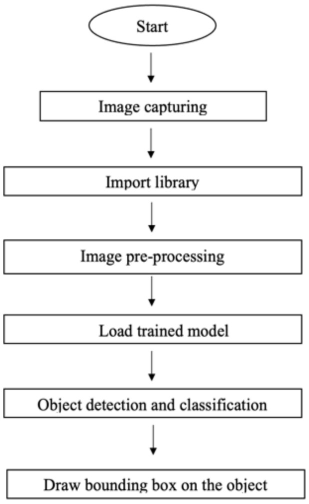



**Fig - 2** : Proposed Methodology

**Image Capturing:** In this step image captured from an Xray.

**Import Library:** Respective libraries required are imported.

**Image Pre- Processing:** Acquired images are pre-processed and unwanted data is erased off.

**Load Trained Model:** Trained model is loaded to procced with further implementation.

**Object Detection & Classification:** Object is detected in a frame and classified into different categories based on different models.

**Draw bounding box on the object:** A box with border is built around the affected region.

## 4. OUTCOMES

Screenshots of the final outcome.

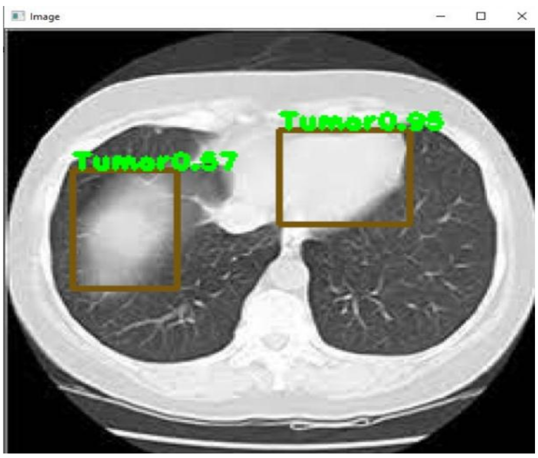



**Fig – 3** : Tomor Detected in Lungs


**Fig – 4** : Clot Detection in Lung

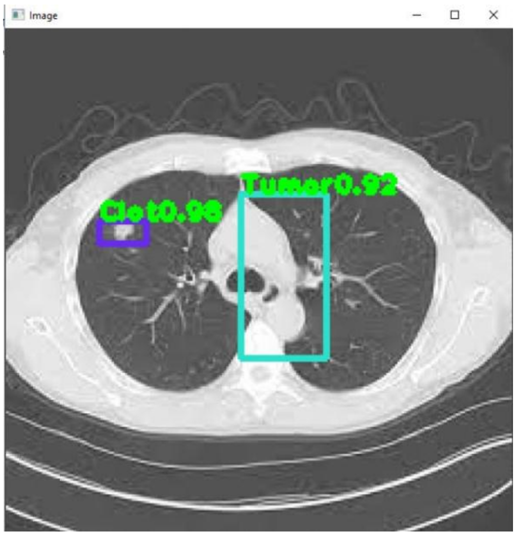



**Fig – 4** : Clot & TumorDetection in Lung

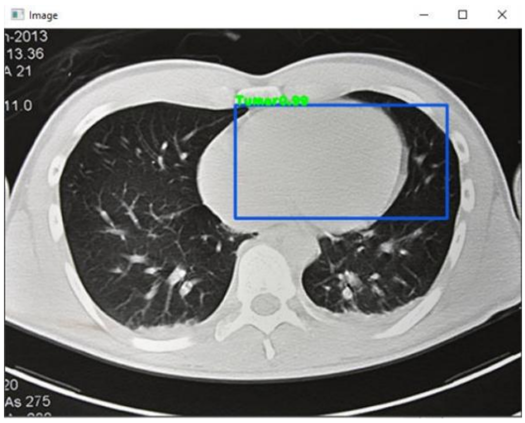
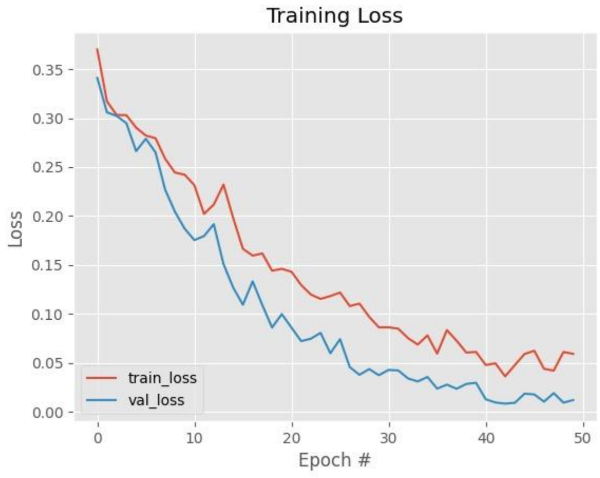



**Fig – 5** : Tumor Detection in Lung




**Graph – 1:** Training Loss


**Graph – 2:** Training Accuracy

## 5. CONCLUSION

System built with YOLO framework is completely useful for detecting any lung cancer related disease. A novel non-small cell lung cancer partition of CT image by, YOLO frame work non-small cell lung cancer partition of CT image can provide precise cancer tumour contours and contribute to the construction of CAD diagnostic systems. Small cell lung cancer is a type of uncontrolled growth tumour that is distinguished by rapid growth and early metastasis spread. A hot topic in the field of medical image analysis is how to effectively design a model for accurate cancer partitioning. Deep learning techniques, particularly deep CNN, have been widely used for medical image partitioning in recent years. The dataset is divided into two parts: testing and training. The training set is further subdivided. 80% of the time is spent on training and 20% on validation. In this paper, we proposed a novel convolution neural network for small cell lung cancer image partitioning and finding the exact location of the tumour attached to the border of blood veins, as well as tumour classification. We are using the deep convolution neural network YOLO framework to pinpoint the exact location of the lung tumour. We intend to expand the dataset in the future by incorporating new lung CT images. In addition, we plan to test the model with an imbalanced dataset and gain more knowledge about updated CNN frameworks. We also plan to volumize the pixel size of the images in the dataset to improve accuracy.

## REFERENCES

[1] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., Lungren, M.P., Ng, A.Y., 2017. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv:1711.05225.

[2] Muhammad Farooq and Abdul Hafeez. Covid-resnet: A deep learning framework for screening of covid19 from radiographs. arXiv preprint arXiv:2003.14395, 2020.

[3] Ezz El-Din Hemdan, Marwa A Shouman, and Mohamed EsmailKarar. Covidx-net: A framework of deep learning classifiers to diagnose covid19 in x-ray images. arXiv preprint arXiv:2003.11055, 2020.

[4] Xiang Yu, Nianyin Zeng, Shuai Liu, and Yu-Dong Zhang. Utilization of densenet201 for diagnosis of breast abnormality. Machine Vision and Applications, 30(7-8):1135–1144, 2019..

[5] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4510–4520, 2018.

[6] Asmaa Abbas, Mohammed M Abdelsamea, and Mohamed Medhat Gaber. Classification of covid-19 in chest x-ray images using detrac deep convolutional neural network. arXiv preprint arXiv:2003.13815, 2020.

[7] Thomas Brox Olaf Ronneberger, Philipp Fischer. U-net: Convolutional networks for biomedical image segmentation. arXiv:1505.04597 [cs.CV], 2015.

[8] North America, R. S. RSNA pneumonia detection challenge. https://www.kaggle.com/c/rsna-pneumonia-detection-challenge/data (2019).

[9] NavdeepKanwal, AkshayGirdhar, and Savita Gupta. Region based adaptive contrast enhancement of medical x-ray images. In 2011 5th International Conference on Bioinformatics and Biomedical Engineering, pages 1–5. IEEE, 2011.

[10] Goodfellow, I., Bengio, Y., Courville, A., Bengio, Y., 2016. Deep learning. volume 1. MIT press Cambridge.

[11] J. Deng, W. Dong, R. Socher, L. Li, Kai Li and Li Fei-Fei, "ImageNet: A large-scale hierarchical image database," 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, 2009, pp. 248- 255, doi: 10.1109/CVPR.2009.5206848.

[12] Gandhi, N., Armstrong, L. J., Petkar, O., & Tripathy, A. K. (2016, July). Rice crop yield prediction in India using support vector machines. In 2016 13th International Joint Conference on Computer Science and Software Engineering (JCSSE) (pp. 1-5). IEEE

[13] Gandhi, N., Armstrong, L. J., & Petkar, O. (2016, July). Proposed decision support system (DSS) for I ndian rice crop yield prediction. In 2016 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR) (pp. 13-18). IEEE.

[14] Islam, T., Chisty, T. A., & Ch akrabarty, A. (2018, December). A Deep Neural Network Approach for Crop Selection and Yield Prediction in Bangladesh. In 2018 IEEE Region 10 Humanitarian Technology Conference (R10-HTC) (pp. 1-6). IEEE.

[15] Jaikla, R., Auephanwiriyakul, S. , & Jintrawet, A. (2008, May). Rice yield prediction using a support vecto r regression method. In 2008 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (Vol. 1, pp. 29-32). IEEE.