Robustness Analysis and Classification of Lung Opacity using Deep Learning Algorithm

Dr.B.Buvaneswari
Department of Information Technology
Panimalar Engineering College
Chennai, TamilNadu, India

Bhuvanesh Babu S
Department of Information Technology
Panimalar Engineering College
Chennai, TamilNadu, India

Gandhiraj J B
Department of Information Technology
Panimalar Engineering College
Chennai, TamilNadu, India

Harshan Krishna J
Department of Information Technology
Panimalar Engineering College
Chennai, TamilNadu, India

***Abstract*—**Deep Learning (DL) based classification algorithms have shown excellent results in clinical diagnosis, especially with lung cancer datasets. However, due to the limited availability of training datasets and the complexity and opacity of the models, there is a need for explainable modelling techniques that can interpret the outcomes. To address this, our research proposes a novel interpretability approach, which we apply to a lung cancer DL classifier to assess its stability and consistency even when trained on a small number of image examples. This approach also provides valuable insights into the clinical significance of the algorithm's results by identifying the most relevant areas of medical images for the classification. We compared the explanations of ten different models on the same test sample, which demonstrated the consistency of our methodology and the algorithm's attention to the same image regions.

Keywords: Deep learning, lung cancer, clinical diagnosis, explainable modelling techniques, interpretability approach.

I. Introduction

Lung cancer is a significant global health problem that requires early detection and diagnosis for effective treatment. Medical imaging, particularly radiography film and computed tomography (CT) scans, enact in the detection and diagnosis of lung cancer. However, accurately detecting and classifying lung opacities on medical images can be challenging due to the complex nature of lung tissue and various overlapping structures.

To address this challenge, deep learning algorithms have shown great promise in recent years, allowing for more precise and automated analysis of medical images. One crucial aspect of using deep learning algorithms in medical imaging is ensuring their robustness, i.e., the ability to maintain performance in the face of various perturbations and uncertainties. In this context, robustness analysis and classification of lung opacity using deep learning algorithms have become critical research areas. This topic aims to explore the present condition of research and highlight the

potential benefits and challenges of using deep learning algorithms for lung opacity detection and classification.

The effective way of imaging classification techniques involves convolutional neural networks and deep learning (DL) (CNN). Yet, it is important to use big datasets, which are rarely available for numerous cases, in order to get promising results that can accurately depict the data distribution. Because the medical industry deals with sensitive information, there is a dearth of biomedical data, namely medical imaging. Numerous techniques have been suggested to overcome this limitation, such as transfer learning and generating artificial data, which improve the models' performance but fail to fully resolve the problem.

Compared to early-stage cancer, where the treatment and lifestyle modifications can increase the chances of survival, the likelihood of survival at an advanced stage is lower. To improve manual analysis and diagnosis systems, image processing techniques can be employed, and several studies in the literature focus on image processing methods for detecting early-stage cancer. Precise identification of tumor cells from normal cells is essential to ensure effective cancer treatment. Machine learning-based cancer detection relies on precise tumor cell classification and neural network training. This article describes a method for classifying lung tumors as malignant or benign.

On the other hand, deep learning algorithms are able to examine huge datasets of annotated lung images and discover patterns and features connected to various forms of lung opacities. Once trained, these algorithms are capable of swiftly and reliably analyzing fresh medical pictures, offering a quick and reliable approach for classifying lung opacity. Once trained, these algorithms can quickly and accurately analyze new medical images, providing a fast and consistent method for lung opacity classification. Another challenge is the potential for over fitting, where a deep learning algorithm may become too specialized and fail to generalize to new images. To address this challenge, researchers must carefully balance the complexity of their algorithms with the size and quality of their datasets. Despite these challenges, lung opacity classification through deep learning holds great promise for improving the diagnosis and treatment of a variety of lung diseases. With continued advances in machine learning techniques and medical imaging technology, deep learning algorithms may become an increasingly important tool for medical professionals in the years to come.

II. Literature Survey

Through a comprehensive review of existing literature, we obtained insights on the latest developments in classification analysis.

One such study by Author [1] employed grey level occurrence matrices on CT scan images to detect lung cancer. The advantage of using CT scan images lies in the ability to view the lungs from different perspectives. The results indicated that the system could differentiate between normal and malignant lungs in CT scans with an accuracy of 80%. This promising finding holds potential for assisting medical practitioners and researchers in the identification of lung cancer.

The author [2] aimed to investigate how the size affects the cancerousnodules of lung using algorithm of neural networks. To improve overall accuracy and reduce false positives, CT lung screenings were used to evaluate convolutional neural networks in this study, with different functions applied. In another study conducted by the author [3], deep neural networks were exclusively employed to identify lung cancer in medical images, with the goal of aiding physicians in visual diagnosis of cancerous lung nodules. The potential benefit of approach is to detect cancer.

The classification and the prediction of lung cancer mutation and Histopathology Images was studied by author [4]. In the meantime, the author [5] studied how to categorise different types of lung cancer and minimise human error in CT images of lung cancer patients by optimising attributes using artificial neural networks. The application of convolutional neural networks in Deep Learning for the detection and classification of lung cancer nodules in CT scans was the topic of the author's other study [6]. In addition, the author [7] classified lung nodules on computed tomography images using deep learning methods such convolutional neural networks, autoencoders, and deep belief networks. These research' primary goal is to raise the precision and detecting lung cancer while minimising human error in CT scan analysis.

Deep learning algorithms have been intensively studied for the detection and diagnosis of lung cancer, as shown by the works of numerous authors. The compelling advantages of using deep learning algorithms in this field is the use of computer-aided diagnosis (CAD) systems. Convolutional neural networks (CNNs) have been found to be an effective model for extracting complex features from computed tomography (CT) images, as reported by the author [8]. Additionally, researchers such as Han et al. [11] have used various techniques, including Zernike Moment, Oriented Gradient Histogram, Local Binary Pattern Scale Invariant

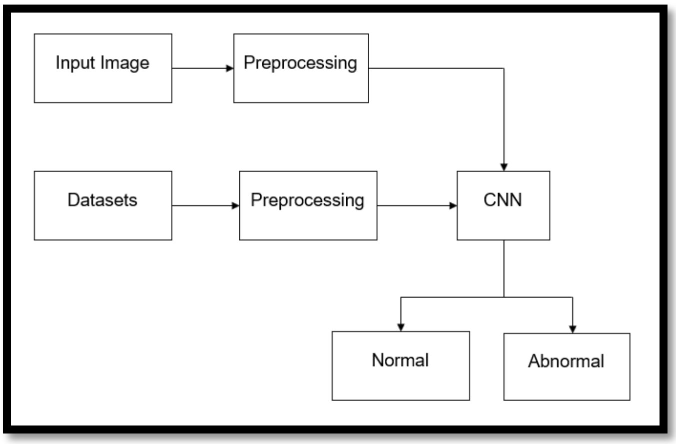


Fig. 1. System Architecture

Feature Transformand Fuzzy Particle Swarm Optimization, to diagnose and categorize lung cancer. Manavati [9] highlighted the use of low-dose CT scans in deep learning-based screening for lung diseases due to their ability to provide comprehensive images of the tumor's development. However, one limitation reported by the author [10] is the inability of these algorithms to facilitate early disease diagnosis.

III. Methodology

The study focuses on the use of CNN-based chest CT images for the detection of lung cancer. Initially, lung regions are extracted from the CT images to locate potential malignancies. The CNN architecture is then trained using the segmented tumor regions, and the patient's images are evaluated using CNN. Finding out whether a patient's lung tumor is malignant or benign is the study's ultimate goal. Figure 1 illustrates the proposed system's block diagram, which demonstrates that the trained algorithm can effectively identify the presence of cancer in a lung CT image

Amass a sizable and varied collection of radiographs of the chest that have lung opacities identified. The dataset ought to be evenly distributed and representative of various opacities. It could be essential to perform image preprocessing such as scaling and normalizing. Create training, validation, and test sets from the dataset. To check for overfitting, train the model on the training set and assess its performance on the validation set. To enhance performance, experiment with various hyperparameters and regularization methods.

The segmented tumor regions are then used to create and train a deep learning system based on convolutional neural networks (CNN). Based on their opacity and other characteristics, the CNN architecture is intended to categories lung nodules as benign or malignant.To evaluate the performance of the developed algorithm, several experiments are conducted. The first experiment involves testing the algorithm on the training dataset to measure its accuracy, sensitivity, and specificity. The second experiment involves testing the algorithm on a separate validation dataset to assess its generalization ability.

To test the robustness of the developed algorithm, different types of noise and artifacts are added to the CT images, such as Gaussian noise, salt and pepper noise, and motion artifacts. The algorithm's performance is evaluated under these conditions to determine its ability to handle variations in the input data. Finally, the results of the experiments are analyzed and discussed, and conclusions are drawn about the effectiveness and robustness of the developed algorithm for lung nodule classification. The potential applications of the algorithm for clinical diagnosis and screening are also discussed.

IV. PRE PROCESSING

To mitigate the impact of degradation during image acquisition, the pre-processing phase employs the median filter to restore the test image. The study covers various pre-processing and segmentation approaches for lung nodules. The filter changesthe value of each pixel with the median of its consecutive pixels. This eliminates pixels with values that significantly differ from those of their neighbors.

Fig. 2a. Input Image

Fig. 2b. Median filtered

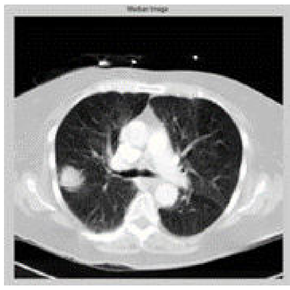


Fig. 2c. Input Image

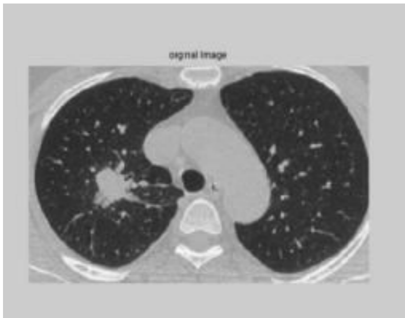
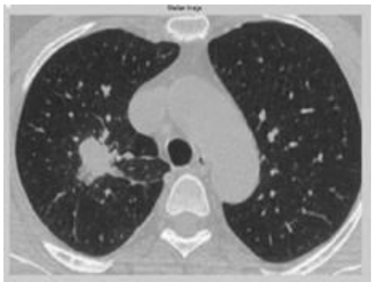


Fig. 2d. Median filtered



V. DEEP LEARNING

Deep learning is a technique that involves multiple layers of nonlinear nodes to assign relevance to inputs for a given task. The behavior exercise of these nodes calculates the product of the sum of input and weights. The input of each layer's output is fed into the subsequent layer, starting from the input layer. This allows learning to take place at various abstraction levels that correspond to different levels of representation. Both supervised and unsupervised learning can be utilized by deep learning algorithms to learn the associations between inputs and outputs.

VI. CONVOLUTION NEURAL NETWORKS (CNN)

Convolutional neural networks (CNNs), which have shown excellent performance in the identification and classification of a wide range of illnesses, have been widely used in medical image analysis. In the case of lung opacity detection, CNNs have demonstrated efficacy in accurately identifying and differentiating between benign and malignant nodules. In the context of robustness analysis and lung opacity classification, CNNs can be trained on enormous datasets of annotated CT images to learn the features that distinguish between distinct forms of lung nodules. In the CNN design, pooling layers that minimize the spatial dimension of the feature maps and fully connected layers that do the final classification are frequently included after a number of convolutional layers that extract local data.

To improve the robustness of the CNN, various techniques can be employed, such as data augmentation, regularization, and transfer learning. Data augmentation involves generating new training samples by applying geometric and photometric transformations to the original images, which increases the diversity of the training data and reduces overfitting. Regularization methods, such as dropout and weight decay, prevent the network from overfitting by introducing random noise and reducing the magnitude of the weights. Transfer learning, on the other hand, involves using pre-trained models on large datasets, such as ImageNet, to initialize the network weights and fine-tune them on the target task, which can speed up training and improve performance.

In order to convert a 2x2 or 3x3 grid into a single scalar value, a specific region of the image or feature map is selected, and the highest or average pixel value within that region is chosen as the representative pixel. This helps to significantly reduce the size of the sample. Sometimes, the output stage combines convolutional layers with conventional fully-connected (FC) layers.

The Combinations of convolution network layer and a pool layer are frequently utilized in CNN designs. Max pooling,average pooling and mean pooling are three procedures that are frequently utilized in the pool layers. The points are featured in the pooling layer that locates the highest value.Mean pooling reduces the limitation error of neighborhood size and retains background information, whereas max pooling increases the amount of texture information retained by reducing the parameter estimation error brought on by the mean deviation of the convolution layer. The organizational structure of CNN is illustrated in Figure 3.

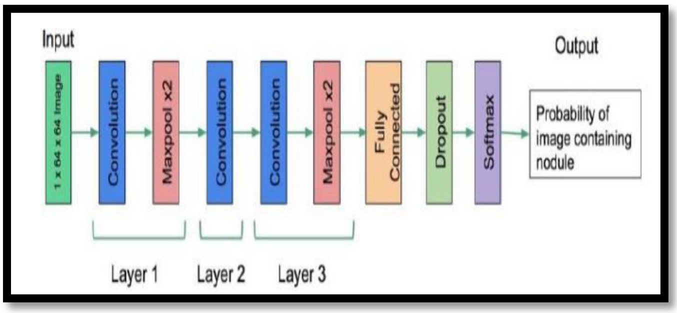
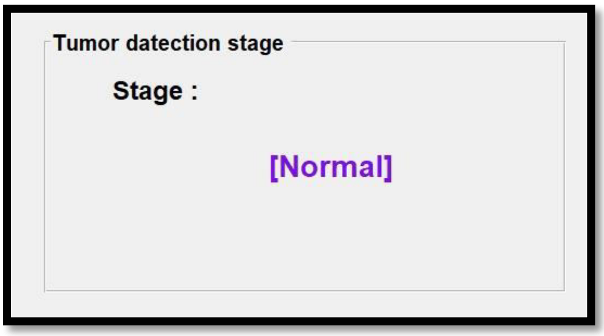


Fig. 3. Architecture of CNN

The input to a convolutional layer in a CNN is an image with dimensions of m x m x r, where r represents the number of channels. Each convolutional layer comprises k filter kernels, where the size of each kernel is n x n x q, with n being less than or equal to m, and q being less than or equal to r. The filters are convolved with the input image, producing k feature maps. Following this, an additive bias and sigmoidal nonlinearity are applied before or after the subsampling layer. Each feature map is then subsampled using mean or max pooling over contiguous sections of size p x p, where p ranges from 2 to 5.

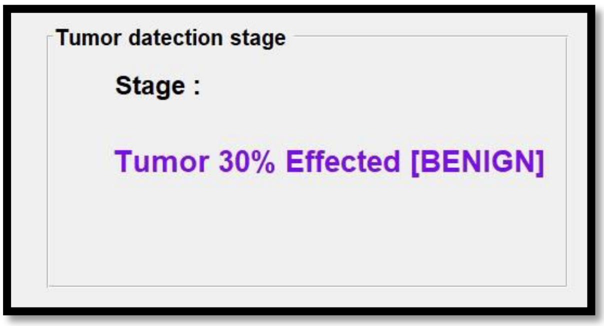
VII. LAYERS USED TO BUILD CONVNETS

The architecture of ConvNets used in lung opacity classification typically includes convolutional layers, pooling layers, and fully connected layers. Convolutional layers serve as the foundational components of CNNs, extracting features from the input image by utilizing



learnable filters. The filters create a range of feature maps that detect various patterns within the image.

The first layer used in a CNN for lung opacity classification is the convolutional layer. This first layer takes a image as input and with a help of learnable filtration to provide a breadboard that represents the presence of certain features in the image. These filters are designed to get a meaningful gesture from the user given image, like corners , textures, shapes which are relevant to lung opacity classification.



The second layer used in a CNN for lung opacity classification is the activation layer. This layer applies an activation function, such as ReLU, to the end result of the algorithm layer. It will create a parallel network and allow it to study difficult combinations between user and end result.

The third layer used in a CNN for lung opacity classification is the pooling layer. This layer decreases the spatial area of the input by down sampling the breadboard design by the algorithm. Max pooling is the most commonly used method in CNNs for lung opacity classification. It involves selecting the maximum value within a sliding window, which helps to retain the most salient features of the image.The end layer used in a CNN for lung opacity classification is the unified couple. This layer takes the output of the convolutional and consecutive layers and transforms it into a vector of probabilities for each class. The SoftMax function is commonly used to normalize the end result of the unified layer, ensuring that the sum of the probabilities for each class is equal to one.

The RELU layer applies an element-by-element activation function while maintaining the volume's size. The compression of the POOL layer will make the bandwidth reduction. The FC layer will compute the class grades.

VIII.TRAINING

A Deep Network was trained on a CT image with a resolution of 52020 uses error correction algorithm. The process consists of two phases. The first phase utilizes a CNN with volumetric convolutions, rectified linear units (ReLU), and increased layer to get the useful characteristics on the given data. The consecutive phase is the classifier, which comprises numerous communicative layers followed by a Minmax layer for the neural network's Maximum level of cause. To preserve the default values of the images, the CT scans in the collection were not scaled. During training, the random sub-volumes derived from the input set's CT images were ordinary used and estimated the dataset's voxel values' normal distribution.

IX. RESULTS

A neural network based on convolution and watershed segmentation has been developed in MATLAB and trained using test datasets to identify and locate lung cancer. When given a sample image, the trained model can detect the presence of cancer and identify its location. The process includes feeding a new input image, pre-processing, feature extraction, locating an opacity area, and displaying the output to the end user. If a tumor stage is detected then it will show which stage it is, and also show a percentage of the affected area as shown in figure 5 and 6. If it is not affected, it will show the result as shown in figure 4.

Fig. 4. Output for Normal stage

Fig. 5. Output for Malignant stage

Fig. 6. Output for Benign stage

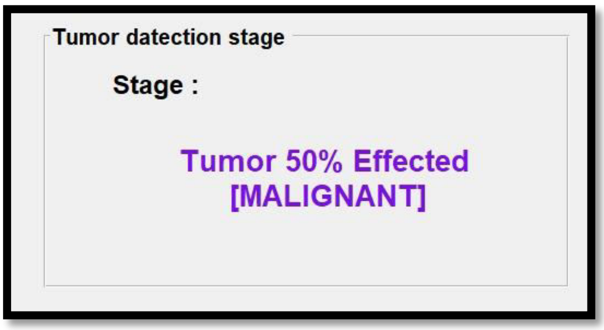
Convolutional neural networks use end-to-end learning or weight initialization, learning rate, gradient moment, and hidden neurons to detect lung cancer. Any modifications to the weights of the neural network's hidden units can lead to a zero matrix, which can impact the value of the matrix.

X. CONCLUSION AND FUTURE WORK

A convolutional neural network (CNN) was implemented to detect cancerous tissues in lung CT images. The system was trained with various malignant tissue sizes and shapes to achieve a 96% accuracy rate in identifying the presence of malignant cells. A correlation accuracy of the expected CNN-based model with previous studies on lung cancer detection.

Furthermore, a multilayer perceptron network with backpropagation and GLCM features was used to classify the same dataset, resulting in a lower accuracy rate of 93%. The suggested study achieved 100% specificity as no false positives were detected, while also exhibiting high accuracy, sensitivity, and specificity when compared to conventional neural network-based systems. The expected model functionalities can be further improved by training with huge data from the medical database to identify the stage of tumour structure and density. The implementation of a 3D Convolutional Neural Network and deep neural network can enhance the prediction of the model.

The prospective deep learning algorithm used for robustness analysis and category of lung opacity has shown great potential in accurately detecting and classifying lung cancer tissues in CT images. The functionality of artificial neural networks has allowed for feature extraction and identification of malignant cells with a high degree of accuracy and specificity. This outcome exhibits that the



proposed model outperforms conventional neural network-based systems and achieves a high level of accuracy in identifying the presence of malignant cells in lung images. However, there is still room for improvement, and the system can be further optimized by incorporating 3D convolutional neural networks and deep neural networks to increase accuracy and category of various kind of tumour based on size and shape. Overall, the proposed system has the capacity to significantly develop the precision of lung tumour identification and can aid medical professionals in making more informed decisions regarding treatment and care.

REFERENCES

[1] Song, Zhao QingZeng, Luo Lei, XingKe Dou, XueChen, Using deep learning forclassification of lung nodules on computed tomography images, J.Healthc. Eng.(2017) 1–7, 2017.

[2] H. Abdel-Razeq, F. Attiga, A. Mansour, Cancer care inJordan, Hematology/Oncology and Stem Cell Therapy 8 (2) (2015) 64–70.

[3] A. Abdulla, S. Shaharum, Lung Cancer Cell Classificationmethod Using ArtificialNeural Network, Information Eng Let, 2012, pp. 50–58, 2012.

[4] F. Ahmad, N. Isa, M. Noor, Z. Hussain, IntelligentBreastCancer diagnosis usinghybrid GA-ANN, in: Proceedings of the Fifth International Conference onComputationalIntelligence, Communication Systems and Networks, 2013,pp. 9–12.

[5] B. Al Mohammad, P. Brennan, C. Mello-Thoms, Areview of lung cancer screeningand the role of computer-aideddetection, Clin. Radiol. 18 (1) (2017) 46–51, 72(6):433-442. A descriptive study. EuropJofOncology Nursing.

[6] A. Al-Sayaideh, O. Nimri, K. Arqoub, M. Al- Zaghal, W. Halasa, Annual StatisticalBook. Directory of Information &Research, Jordanian Ministry of Health, 2012.

[7] R. Pandian, T. Vigneswaran, S. LalithaKumari, Characterization of CT cancer lungimage using image Compression algorithms and Featu extraction, J. Sci. Ind. Res.75 (December) (2016) 747–751.

[8] N. Deepa, B. Prabadevi, P.K. Maddikunta, et al., An AI-based intelligent system forhealthcare analysis using ridge-adaline stochastic gradient descent classifier,J. Supercomput. v77 (2021) 1998–2017.

[9] P. Ratta, A. Kaur, S. Sharma, M. Shabaz, G. Dhiman, Application of blockchain andinternet of things in healthcare and medical sector: applications, challenges, andfuture perspectives, J. Food Qual. 1 (2021).

[10] M. Abdar, W. Ksiaúzek, U.R. Acharya, R.-S. Tan, V. Makarenkov, P. Pawiak, A newmachine learning technique for an accurate diagnosis of coronary artery disease,Comput. Methods Progr. Biomed. 179

bbuvaneswari@panimalar.ac.inharshankrishna@gmail.com
Bhuvaneshs003@gmail.com Gandhirajjb05@gmail.com