Advanced CNN Modifications for Detection of Lung Cancer from CT Scan Images

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Abstract

Medical imaging tools are essential in early-stage lung cancer diagnostics and the monitoring of lung cancer during treatment. Various medical imaging modalities, such as chest X-ray, magnetic resonance imaging, positron emission tomography, computed tomography, and molecular imaging techniques, have been extensively studied for lung cancer detection. These techniques have some limitations, including not classifying cancer images automatically, which is unsuitable for patients with other pathologies. It is urgently necessary to develop a sensitive and accurate approach to the early diagnosis of lung cancer. Deep learning is one of the fastest-growing topics in medical imaging, with rapidly emerging applications spanning medical image-based and textural data modalities. With the help of deep learning-based medical imaging tools, clinicians can detect and classify lung nodules more accurately and quickly. Therefore, this work implements the advanced modifications in CNN model for the detection of lung cancer from chest scan images. The proposed CNN model is able to classify the benign and malignant i.e., normal, and cancerous with higher accuracy as compared to state-of-the-art machine learning approach called support vector machine (SVM) classifier. In addition, the obtained quality metrics discloses the superiority of proposed deep CNN model for assisting the expertise in an enhanced diagnosis.

Keywords: Support vector machine, convolutional neural network, lung cancer classification.

1. Introduction

Lung cancer is the primary cause of cancer death worldwide, with 2.09 million new cases and 1.76 million people dying from lung cancer in 2018 [1]. Four case-controlled studies from Japan reported in the early 2000s that the combined use of chest radiographs and sputum cytology in screening was effective for reducing lung cancer mortality. In contrast, two randomized controlled trials conducted from 1980 to 1990 concluded that screening with chest radiographs was not effective in reducing mortality in lung cancer [2, 3]. Although the efficacy of chest radiographs in lung cancer screening remains controversial, chest radiographs are more cost-effective, easier to access, and deliver lower radiation dose compared with low dose computed tomography (CT). A further disadvantage of chest CT is excessive false positive (FP) results. It has been reported that 96% of nodules detected by low-dose CT screening are FPs, which commonly leads to unnecessary follow-up and invasive examinations. Chest radiography is inferior to chest CT in terms of sensitivity but superior in terms of specificity. Taking these characteristics into consideration, the development of a computer-aided diagnosis (CAD) model for chest radiograph would have value by improving sensitivity while maintaining low FP results [4]. Many computer-aided detection (CAD) systems have been extensively studied for lung cancer detection and classification [5, 6]. Compared to trained radiologists, CAD systems provide better lung nodules and cancer detection performance in medical images. Generally, the CAD-based lung cancer detection system includes four steps: image processing, extraction of the

region of interest (ROI), feature selection, and classification. Among these steps, feature selection and classification play the most critical roles in improving the accuracy and sensitivity of the CAD system, which relies on image processing to capture reliable features. However, benign, and malignant nodule classification is a challenge. Therefore, a rapid, cost-effective, and highly sensitive deep learning-based CAD system for lung cancer prediction is urgently needed.

The recent application of convolutional neural networks (CNN), a field of deep learning (DL), has led to dramatic, state-of-the-art improvements in radiology. DL-based models have also shown promise for nodule/mass detection on chest radiographs, which have reported sensitivities in the range of 0.51–0.84 and mean number of FP indications per image (mFPI) of 0.02–0.34. In addition, radiologist performance for detecting nodules was better with these CAD models than without them. In clinical practice, it is often challenging for radiologists to detect nodules and to differentiate between benign and malignant nodules. Normal anatomical structures often appear as if they are nodules, which is why radiologists must pay careful attention to the shape and marginal properties of nodules. As these problems are caused by the conditions rather than the ability of the radiologist, even skilful radiologists can misdiagnose. Therefore, the main purpose of this work was to train and validate a DL-based model capable of detecting lung cancer on chest radiographs, and to evaluate the characteristics of this DL-based model to improve sensitivity while maintaining low FP results.

2. Literature Survey

The development of malignant cells in the lungs is known as lung cancer. Overall men and women's mortality rates have increased as a result of growing cancer incidence. Lung cancer is a disease wherein the cells in the lungs quickly multiply. Lung cancer cannot be eradicated, but it can be reduced [7]. The number of people affected with lung cancer is precisely equal to the number of people who smoke continuously. Lung cancer treatment was evaluated using classification approaches such as Naive Bayes, SVM, Decision Tree, and Logistic Regression. Pradhan et al. [8] conduct an empirical evaluation of multiple machine learning methods that can be used to identify lung cancer using IoT devices. A survey of roughly 65 papers employing machine learning techniques to forecast various diseases was conducted in this study. The study focuses on a variety of machine learning methods for detecting a variety of diseases in order to identify a gap in prospective lung cancer detection in medical IoT. Deep residual learning is used by Bhatia et al. [9] to identify lung cancer from CT scans. With the UNet and ResNet algorithms, we propose a series of pre-processing approaches for emphasising cancer-prone lung regions and retrieving characteristics. The extracted features are fed through several classifiers, namely Adaboost and Random Forest, and the individual predictions are ensembled to calculate the likelihood of a CT scan becoming cancerous.

Without learning inadequate human information, Shin et al. [10, 11] use deep learning to investigate the characteristics of cell exosomes and determine the similarities in human plasma extracellular vesicles. The deep learning classifier was tested with exosome SERS data from regular and lung cancer cell lines and was able to categorise them with 95% efficiency. The deep learning algorithm projected that 90.7% of patients' plasma exosomes were more similar to lung cancer cell extracellular vesicles than the mean of healthy controls in 43 patients, encompassing stage I and II cancer patients. In the ability to forecast lung ADC subtypes, researchers looked at four clinical factors: age, sex, tumour size, and smoking status, as well as 40 radiomic markers. The LIFEx software was used to extract radiomic characteristics from PET scans of segmented cancers. The clinical and radio mic variables were ranked, and a subset of meaningful features was chosen based on Gini coefficient scores for histopathological class relationships [12]. In the estimation of survival, a deep learning network with a tumour cell and metastatic staging system was used to examine the dependability of

individual therapy suggestions supplied by the deep learning preservation neural network. The C statistics were employed to evaluate the performance of the model. The computational intelligence survival neural network model's longevity forecasts and treatment strategies were made easier with the use of a customer interface [13]. A lung cancer detection model that utilizes image analysis and machine intelligence to identify the occurrence of lung cancer in CT scans and blood tests has been developed. Despite the fact that CT scan findings are more efficient than mammograms, patient CT scan pictures are divided into normal and abnormal categories [14, 15]. Even in the same tumour stage, non-small-cell cancer patients have a wide range of clinical performance and results. This research investigates deep learning applications such as medical imaging, which could help with patient stratification by automating the measurement of radiographic properties.

3. Proposed system model

Activity diagram is another important diagram is used to describe the dynamic aspects of the system as shown in Figure 1.
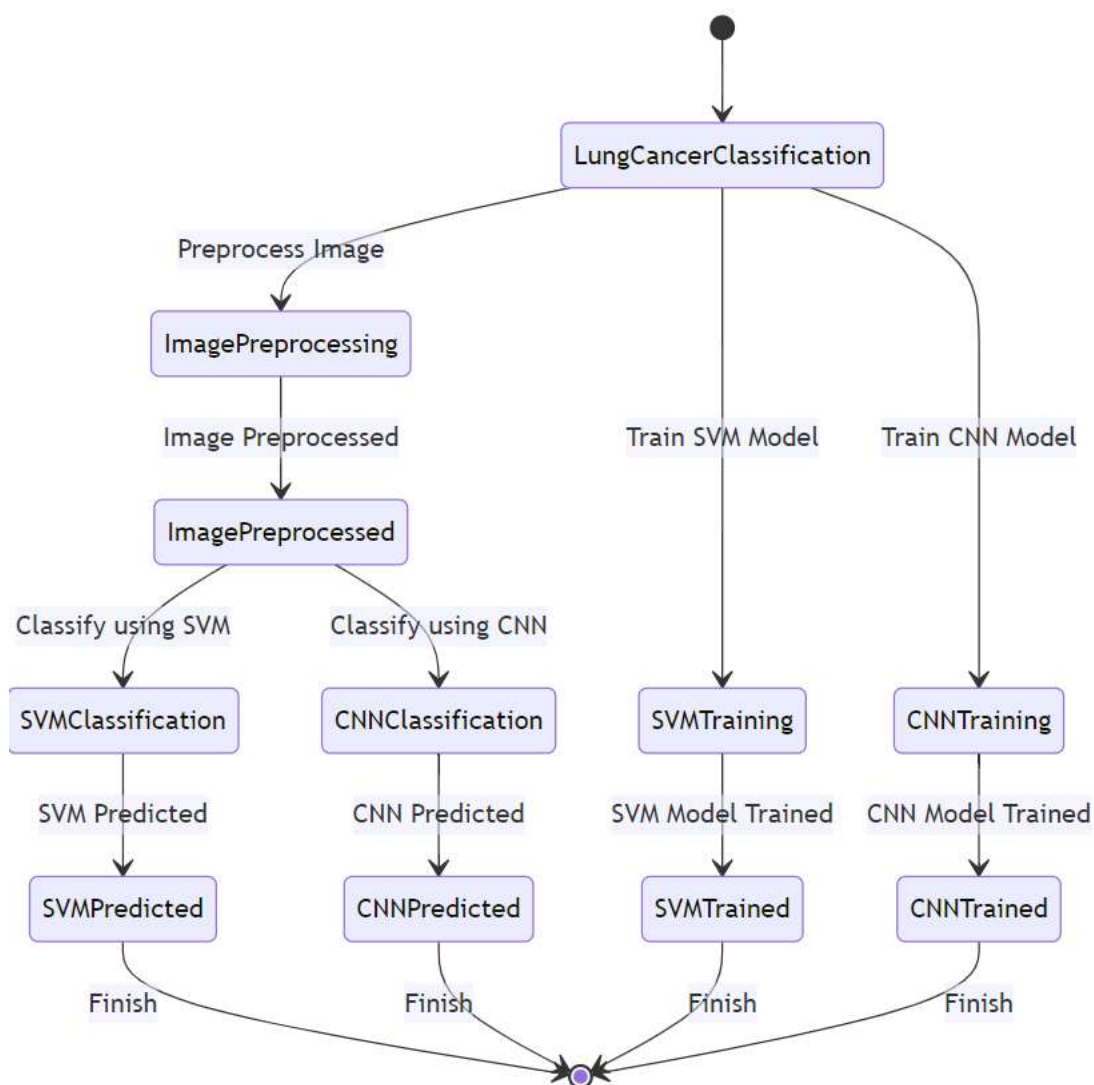

Figure 1. Proposed System Model

According to the facts, training and testing of proposed model involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the

objects with probabilistic values ranging from [0,1]. Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.
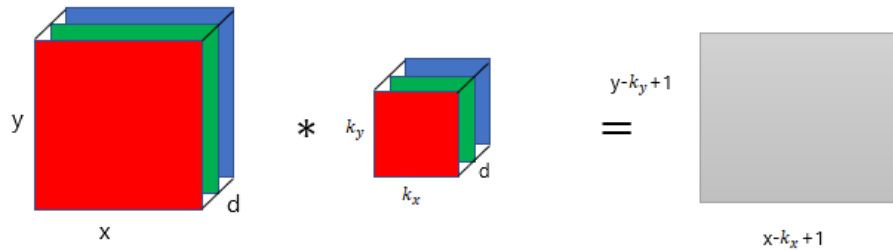

Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.
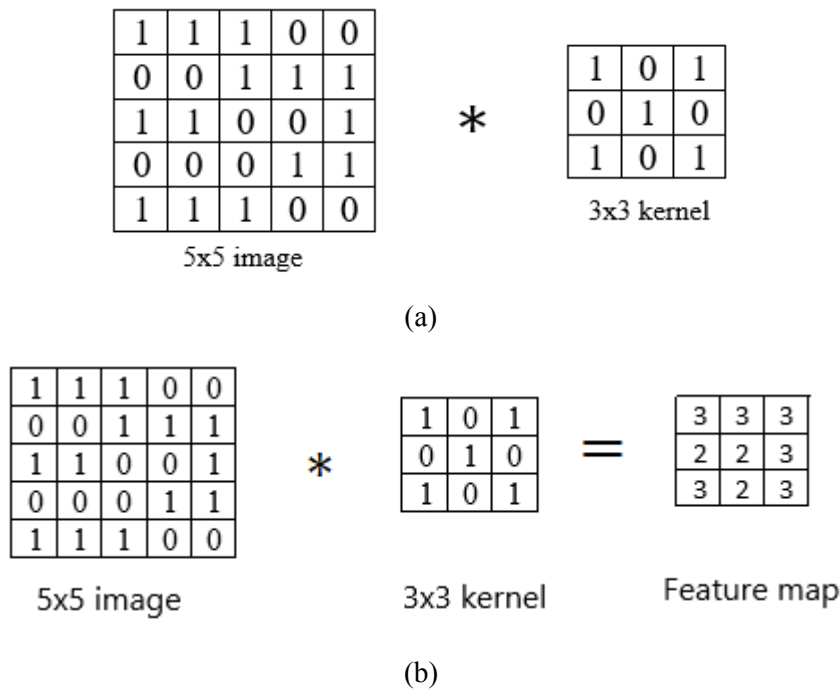

(a)

(b)

Fig. 3: Example of convolution layer process (a) an image with size $\mathbf{5 \times 5}$ is convolving with $\mathbf{3 \times 3}$ kernel (b) Convolved feature map

ReLU layer: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Softmax classifier: Generally, as seen in the above picture softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

4. Results description

This project uses a total of 138 CT scan images out of which 80% i.e., 110 images are used for training and 20% i.e., 28 images are used for testing the SVM, and CNN models for detecting the normal, and cancer from test CT scan images. It uses the Tkinter library for creating a graphical user interface (GUI) to perform lung cancer detection and classification tasks using Support Vector Machine (SVM) and Convolutional Neural Network (CNN) models.
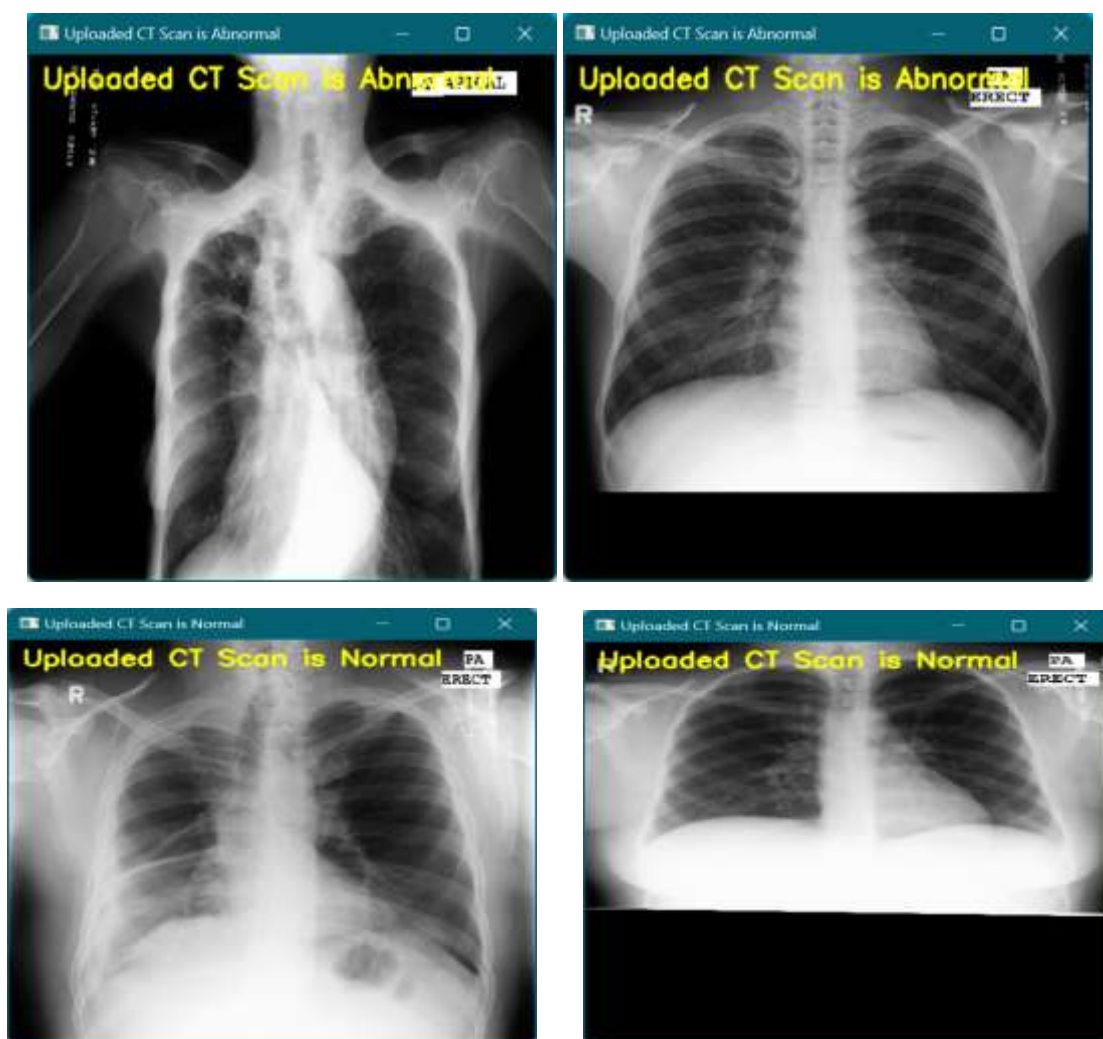

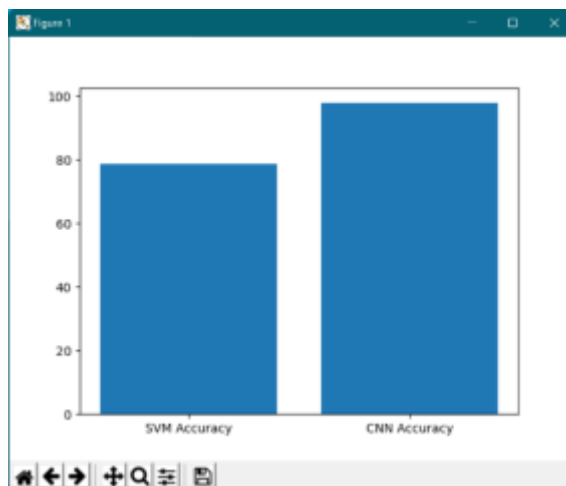Figure 4: Sample prediction outcome obtained using proposed 3D CNN model.

Figure 5: Performance comparison of accuracy for lung cancer detection system using SVM, and proposed 3D CNN model.

5. Conclusion

This work implements an advanced CNN modifications for the detection of lung cancer from CT scan images. The higher accuracy of the 3D CNN can be attributed to its ability to automatically learn relevant features from the images through multiple convolutional layers, which is especially advantageous for complex and high-dimensional data like CT scans. On the other hand, SVM relies on handcrafted features and may struggle with capturing complex patterns in the data. Based on the obtained results, it is clear that the proposed 3D CNN model significantly outperformed the SVM classifier in the task of detecting lung cancer from CT images. The 3D CNN achieved an accuracy of 97.82%, whereas the SVM achieved an accuracy of 78.57%. This indicates that the CNN model is much more effective at classifying CT scan images as either normal or abnormal, which is crucial for the early detection of lung cancer. In conclusion, the promising results obtained by the 3D CNN model in lung cancer detection highlight the potential of deep learning in medical image analysis. Future endeavors should focus on refining model performance, scalability, and seamless integration into clinical workflows, with the ultimate goal of positively impacting patient care and outcomes across various medical domains.

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