Lung Cancer Detection Using Convolutional Neural Network on CT Scan Images

Abstract *Cancer is on the rise globally due to factors like modern technology and increased radiation exposure. There are many different cancers, including lung, breast, prostate, and skin cancers. Lung cancer, however, is particularly deadly and often goes undetected until it's advanced. Early detection and treatment are crucial for patient recovery. Medical professionals use CT Scan images from potentially infected areas of lungs for diagnosis. Most of the time, the diagnosis regarding lung cancer is error-prone and time-consuming. Convolutional Neural networks can identify and classify lung cancer with greater accuracy in a shorter period, which is crucial for determining patients' right treatment procedure and their survival rate. The CNN model training and validation accuracy of 96.11% and* of *82.33% are obtained. The patient is made well aware of the disease and enabled with their health tracking using website.*

Keywords — *Convolutional Neural Network (CNN), Machine Learning, Lung Cancer, CT scan Image*

I. INTRODUCTION

Lung cancer is a prominent cancer affecting both men and women, accounting for nearly 25% of all cancer deaths. Smoking is the primary culprit, responsible for roughly 80% of lung cancer deaths. For non-smokers, lung cancer can be caused by exposure to radon, secondhand smoke, air pollution, workplace hazards like asbestos or diesel exhaust, or certain chemicals.

Several tests are used to detect lung cancer cells and rule out other possibilities, including imaging scans (X-ray, CT scan), sputum cytology (microscopic examination of coughed-up mucus), and tissue sampling (biopsy). While a biopsy is performed, evaluation of the microscopic histopathology slides by experienced pathologists remain essential for diagnosis.

Diagnosing lung cancer and its specific type can be time-consuming for pathologists and other medical professionals. Misdiagnosis, unfortunately, occurs at a significant rate, leading to incorrect treatment and potentially costing patients' lives.

We propose a deep learning approach for lung cancer detection in CT scans. A Convolutional Neural Network (CNN) is implemented to automatically extract key features from the images and identify cancerous cells. The trained model can then be deployed on a website built with Flask, potentially allowing patients to upload their scans and receive information about the predicted presence of lung cancer. This could empower patients with greater awareness of their health and potentially aid in early detection and tracking.

II. LITERATURE REVIEW

- Transfer learning with DenseNet-121 on chest X-rays (74.43% accuracy) by Ausawalaithong et al. Deep Convolutional Neural Network (DCNN) for lung cancer type classification on cytological images (71.1% accuracy) by Atsushi et al.
- Support Vector Machine (SVM) with image processing for lung cancer detection on CT scans (78% accuracy) by Rahane et al.
- Convolutional Neural Networks (CNN) for lung cancer detection on whole slide histopathology images (VGG16: 75.41% accuracy, ResNet50: 72.05% accuracy) by Saric et al.
- CNN for lung cancer detection and classification on CT scans (78% accuracy) by Sasikala et al.
- Probabilistic Neural Network (PNN) with feature selection for lung cancer detection on CT scans (90% accuracy) by Chakravarthy et al.

III. METHODOLOGY

Our proposed system followed data acquisitions, data formatting, model training, testing, and prediction, described in the below sections.

A. Data Acquisition

The CT Scan images are obtained from CT Scan image data set. Two classes with positive or negative carcinoma cells.

B. Data Formatting

The obtained data set was CT Scan images with .jpeg format. The images were resized to maintain a uniform aspect ratio of one with (150, 150) pixel size for the CNN operation. All the pixel values for the images were converted in range of (0, 1) to make convergence faster. We have implemented the image acquisition technique like horizontal and vertical flip and zooming to increase the image number and variation in the data pattern. The neural network tends to over-fit in case of a limited number of training data samples trained with a higher number of epochs (500). Fig. 1(a) shows positive lung Carcinoma cells(unhealthy) Fig. 1(b) shows negative lung Carcinoma cells(healthy) image and its augmented images, respectively, with the horizontal and vertical flip and a zoom range of (0.2-0.5) applied. We also applied features extraction and cross validation technique.

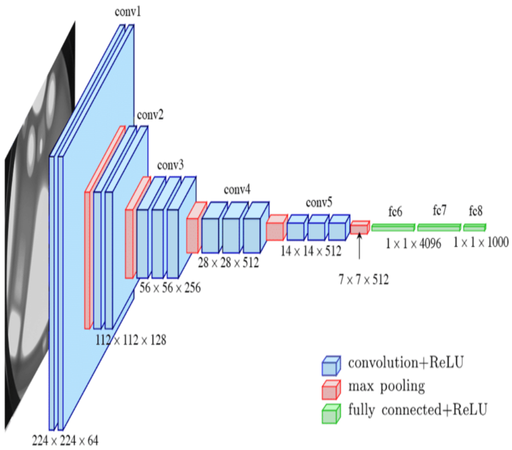
Fig 1(a): Positive lung Carcinoma

Fig 1(b): Negative lung Carcinoma

C. Model Training, Testing, and Prediction

A liner stack of layers was used to create the Convolutional Neural Network (CNNs or Conv Nets) for the image classification and recognition. Training and testing images were passed through convolutional layers with kernel filters, max pooling, and fully connected layers. The sigmoid function was applied to classify the given object. The model was trained and tested using Google Collaboratory GPU.

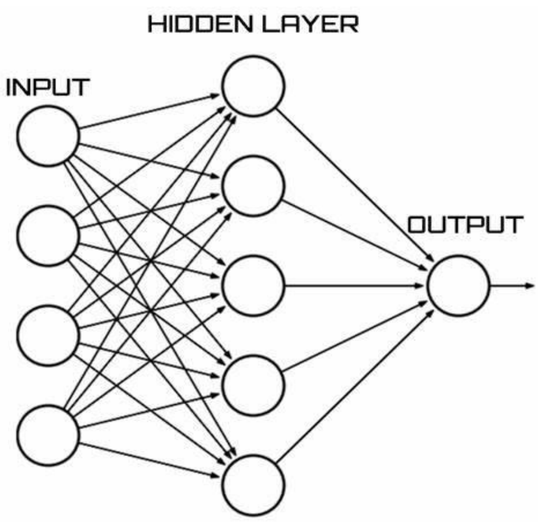
This lung cancer detection system employs a deep learning approach with a custom Convolutional Neural Network (CNN) architecture. The network leverages pre-trained VGG-16 for feature extraction. Here, only the convolutional layers of VGG-16 are utilized, while the densely connected layers are discarded to focus solely on feature learning from the CT scan images.



To enhance model robustness and mitigate overfitting, a k-fold cross-validation technique is implemented during training. This method involves splitting the data into multiple folds, with the model trained on a subset and validated on the remaining ones. This process is iterated for all folds, ensuring a more robust evaluation of the model's generalizability.

The custom CNN architecture, built using TensorFlow, comprises the following layers:

1. Input Layer: Receives preprocessed CT scan images of size (150 x 150 pixels) which passed through VGG-16.
2. Flatten Layer: Transforms the extracted features from VGG-16 into a one-dimensional vector.
3. Dropout Layer: Introduces a dropout rate of 0.5 to prevent overfitting during training.
4. Dense Layer: Contains 32 nodes with a ReLU (Rectified Linear Unit) activation function for improved learning through non-linearity.
5. Output Layer: A single-node Dense layer with a sigmoid activation function predicts the final class probabilities, indicating the likelihood of the image belonging to the "healthy" or "cancerous" category.



The training process utilizes an adaptive moment estimation (RMSprop) optimizer with a learning rate of 1e-5 for efficient parameter updates. Binary cross-entropy (CE) serves as the loss function, measuring the discrepancy between the predicted and labeled outputs.

This combined approach leverages the feature extraction capabilities of a pre-trained model with a custom CNN for classification, aiming to achieve accurate lung cancer detection in CT scans.

The performance of the developed CNN model was measured using the confusion matrix plot, and the metrics accuracy, precision, recall, and f1-score were also calculated as below:

$$Accuray = \frac{(TP + TN)}{(TP + FP + FN + TN)}$$

$$Precision = \frac{TP}{(TP + FP)}$$

$$Recall = \frac{TP}{(TP + FN)}$$

$$F1 - Score = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

$$\text{Accuracy} = \frac{(32+67)}{(32+3+12+67)} = 0.8684$$

$$\text{Precision} = \frac{32}{(32 +3)} = 0.9142$$

$$\text{Recall} = \frac{32}{(32 +12)} = 0.7272$$

$$\text{F1 - Score} = \frac{2*(0.7272*0.9142)}{(0.7272 +0.9142)} = 0.81$$

Where TP, FP, FN, and TN represent the output measures as true positive, false positive, false negative, and true negative values for the training and validation images of the models.

The trained model weights were saved into the hd5 file format and used to predict the future by loading the weights to the model architecture.

IV. RESULT AND DISCUSSION

The images were trained for 500 epochs with batch size 32 with 10 steps in each epoch. The model achieved a training accuracy of 96.11% and a validation accuracy of 82.33% in the final epoch. Test Accuracy 85.08%

Below, Fig. 2(a) shows the plot of model validation accuracy and Fig. 2(b) shows the F1 score of the model.

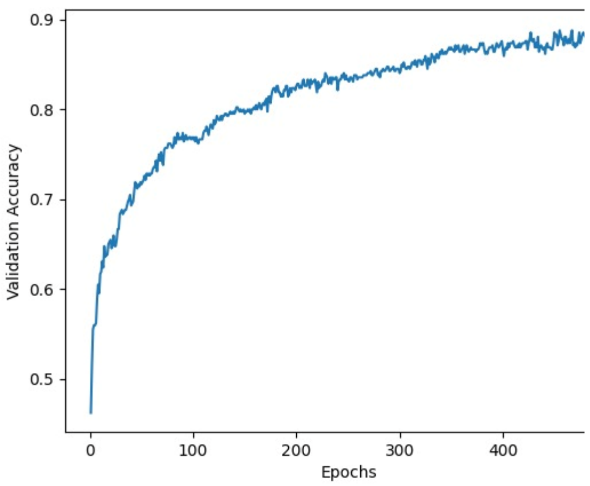


Fig 2(a): Plot of Model validation Accuracy

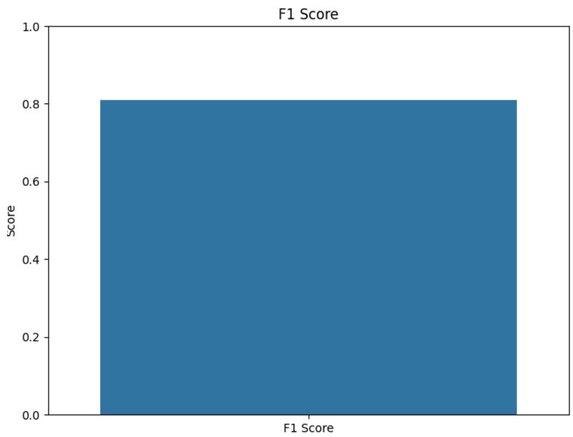


Fig 2(b): F1 score box plot graph

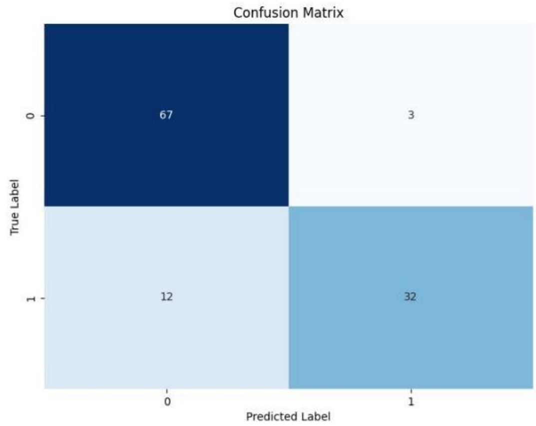


Fig (3): Confusion Matrix of Different Image Categories for Validation Images

The confusion matrix shown in Fig. 3 depicts the true label vs. the predicted label of the images for the validation data in given labeled categories.

V. CONCLUSION

This research work presents lung cancer detection using CT Scan images. A convolutional neural network (CNN) was implemented to classify an image of Two different categories positive and negative cell carcinoma. The model was able to achieve 96.11% and 82.33% of training and validation accuracy. The precision, f1socre, recall were calculated, and a confusion matrix plot was drawn to measure the model performance.

VI. REFERENCES

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