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# LUNG CANCER DETECTION FROM CT IMAGES: LEVERAGING MEDICAL IMAGING TECHNIQUES FOR ACCURATE DIAGNOSIS

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## ABSTRACT

Diagnostics for lung cancer in its early stages and therapy monitoring for lung cancer depend heavily on medical imaging technologies. For the purpose of detecting lung cancer, a number of medical imaging modalities, including computed tomography, magnetic resonance imaging, positron emission tomography, chest X-ray, and molecular imaging approaches, have been thoroughly examined. Some of the disadvantages of these systems include their inability to automatically categorize cancer images, making them inappropriate for use in patients with other illnesses. The development of a sensitive and precise method for the early diagnosis of lung cancer is desperately needed. One of the areas of medical imaging that is expanding the fastest is deep learning, with quickly developing applications involving textural and medical image-based data modalities. Medical imaging technologies based on deep learning can help clinicians identify and categorize lung nodules more rapidly and precisely. Consequently, the sophisticated CNN model modifications are implemented in this study for the purpose of detecting lung cancer from chest scan images. The suggested CNN model outperforms the state-of-the-art support vector machine (SVM) classifier in machine learning when it comes to accurately classifying benign and malignant, or normal and cancerous, tissues. Furthermore, the quality metrics obtained reveal the higher performance of the suggested deep CNN model in supporting the experts in an improved diagnosis.

**Keywords:** Lung Cancer Diagnostics, Deep Learning, Chest X-Ray, Magnetic Resonance Imaging,

## 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.

## 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].

## 3. PROPOSED METHODOLOGY

A deep CNN model for lung cancer classification from CT scan images is a powerful approach that leverages the capabilities of deep learning to automatically learn and extract relevant features from raw image data. Here is an overview of how a deep CNN model can be used for classifying CT scan images into normal and malignant categories:

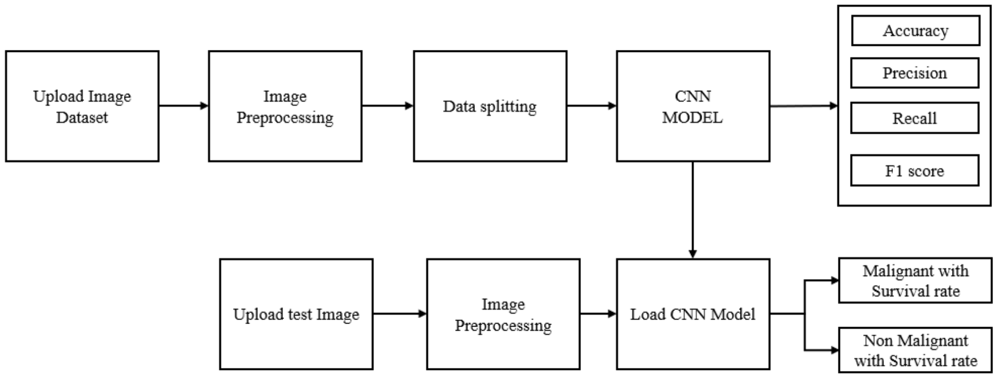


Figure 1: Block Diagram of Proposed Model.

**Convolutional Neural Network**

Convolutional Neural Networks (CNNs) represent a pivotal advancement in deep learning, particularly well-suited for tasks involving structured grid-like data, such as images. Their architecture and design draw inspiration from biological processes, specifically how the visual cortex processes visual information. CNNs have revolutionized fields like computer vision, enabling breakthroughs in image classification, object detection, and segmentation, among others.

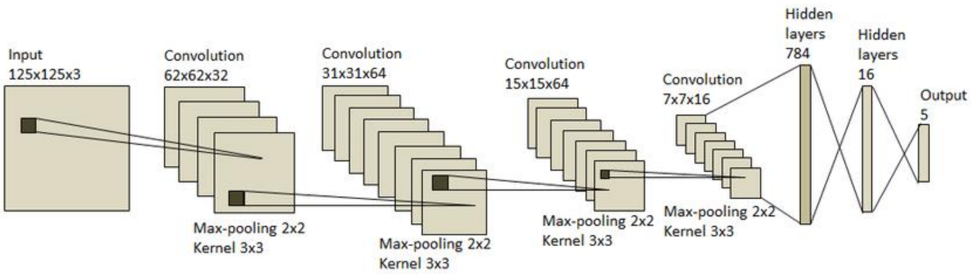


Figure. 2: Architectural Diagram of CNN Model.

**Components of a CNN**

**1. Input Layer**

The input to a CNN is typically an image represented as a grid of pixel values. For a color image, this might be a 3D array (height x width x 3) where 3 represents the RGB channels.

**2. Convolutional Layer**

The convolutional layer applies filters (kernels) to the input image. Each filter performs convolution operation, which involves sliding the filter matrix over the input image and computing dot products to produce a feature map. Mathematically, for a 2D input image I and a filter K, the convolution operation at a specific position (i,j) is given by:

$$(I*K)(i,j) = \sum m \sum n I(m,n) \cdot K(i-m,j-n)$$

where I(m,n) represents the pixel intensity at position (m,n) in the input image.

**3. Activation Function**

After convolution, an activation function like ReLU (Rectified Linear Unit) is applied element-wise to introduce non-linearity into the model:

$$ReLU(x)=max(0,x)$$

ReLU helps CNNs learn complex patterns and improves convergence during training.

**4. Pooling Layer**

Pooling layers (e.g., max pooling or average pooling) follow convolutional layers to reduce spatial dimensions of the feature maps, thereby decreasing computational complexity and controlling overfitting.

For max pooling, the operation extracts the maximum value from each patch of the feature map:

$$MaxPooling(I)(i,j)=maxm,nI(m,n)$$

**5. Flattening**

After several convolutional and pooling layers, the resulting feature maps are flattened into a vector. This step converts the 2D or 3D matrix representation into a 1D vector that can be input to fully connected layers.

**6. Fully Connected (Dense) Layers**

These layers process the flattened features. Each neuron in a fully connected layer is connected to every neuron in the previous layer. Mathematically, for a layer l with output vector $h^{(l)}$ and weights $W^{(l)}$ the output $z^{(l+1)}$ of the next layer is computed as:

$$z^{(l+1)} = W^{(l)}h^{(l)}+b^{(l)}$$

where $b^{(l)}$ is the bias vector.

**7. Output Layer**

The final layer of the CNN produces the network's output. For classification tasks, this typically involves applying a softmax activation function to the output of the last fully connected layer. Softmax normalizes the outputs into probabilities across multiple classes, enabling the model to make predictions.

**8. Loss Function**

A loss function quantifies how well the network's predictions match the actual target values during training. For classification tasks, cross-entropy loss is commonly used.

**9. Optimization**

To minimize the loss function and improve the network's performance, optimization algorithms like stochastic gradient descent (SGD) or its variants (e.g., Adam, RMSProp) are employed. These algorithms adjust the weights and biases of the network iteratively based on the gradients computed during backpropagation.

**10. Backpropagation**

Backpropagation is a key mechanism in CNNs for computing the gradients of the loss function with respect to each parameter in the network. It propagates these gradients backward through the network, allowing efficient updates of the model's weights and biases,

**4. RESULTS AND DISCUSSION**

Figure 3 shows that Presents a collection of images sourced from a dataset categorized as Non-Malignant class. Each image visibly represents lung tissue devoid of any cancerous manifestations, serving as representative samples for this class in the dataset.

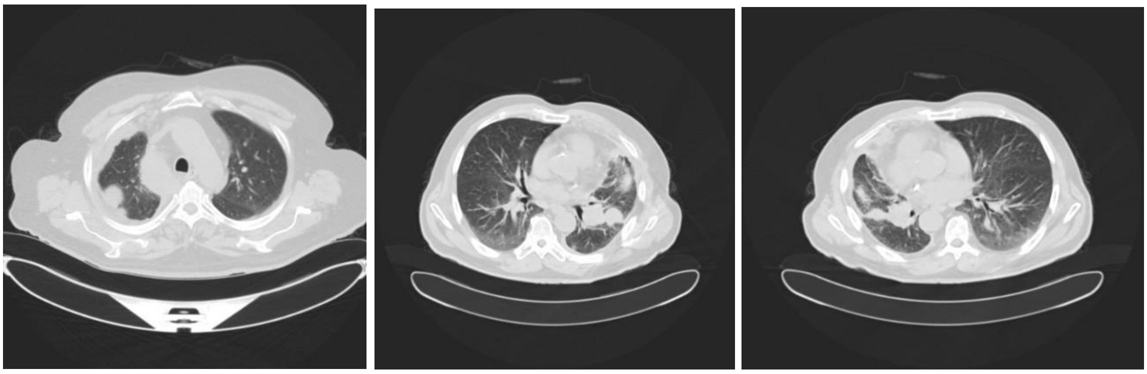

Figure 3: Sample images from dataset with Non-Malignant class.

Figure 4 shows that Exhibits a series of images sourced from a dataset categorized as Malignant class. Each image conspicuously showcases lung tissue displaying cancerous growth or abnormalities, thereby serving as exemplars for this category within the dataset. Figure 5 shows Depicts the visual layout of a user interface (UI) tailored for the explicit purpose of detecting instances of lung cancer within images. This UI encompasses various interactive elements and functionalities aimed at facilitating the process of image-based lung cancer detection.

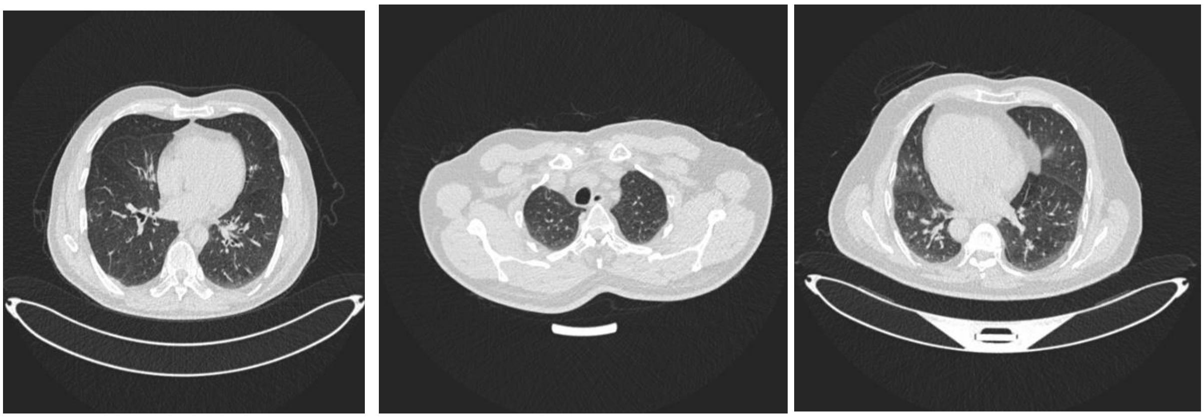

Figure 4: Sample images from dataset with Malignant class.

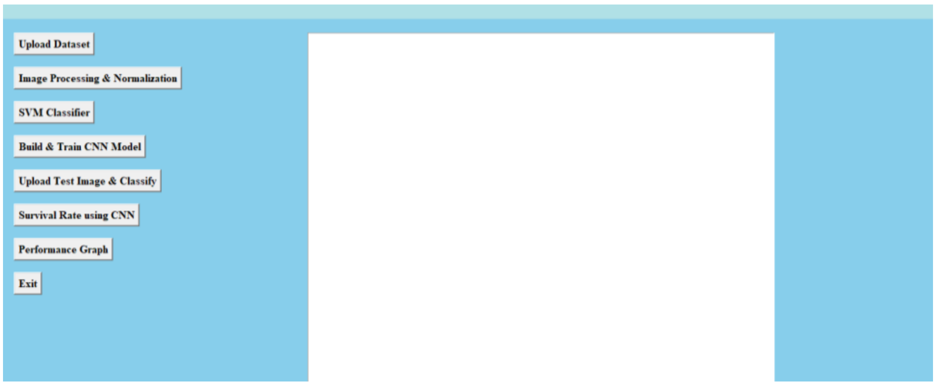


Figure 5: sample UI used for Lung cancer detection from images


Figure 6: UI shows the data after image preprocessing

Figure 6 shows Demonstrates the visual representation of data presented within the UI subsequent to undergoing a series of preprocessing steps. These preprocessing steps typically involve image enhancements, corrections, or feature extraction techniques aimed at optimizing the images for subsequent analysis and detection tasks. Figure 7 shows Illustrates the graphical depiction of the performance metrics attributed to a Support Vector Classifier (SVM) utilized for the task of lung cancer detection. These metrics may include accuracy, precision, recall, or F1-score, indicating the efficacy of the SVM model in distinguishing between cancerous and non-cancerous lung tissue. Figure 8 Exhibits a visual representation of the confusion matrix corresponding to the performance evaluation of the SVM Classifier. This confusion matrix offers a comprehensive breakdown of the classifier's predictive performance, including true positive, false positive, true negative, and false negative classifications.

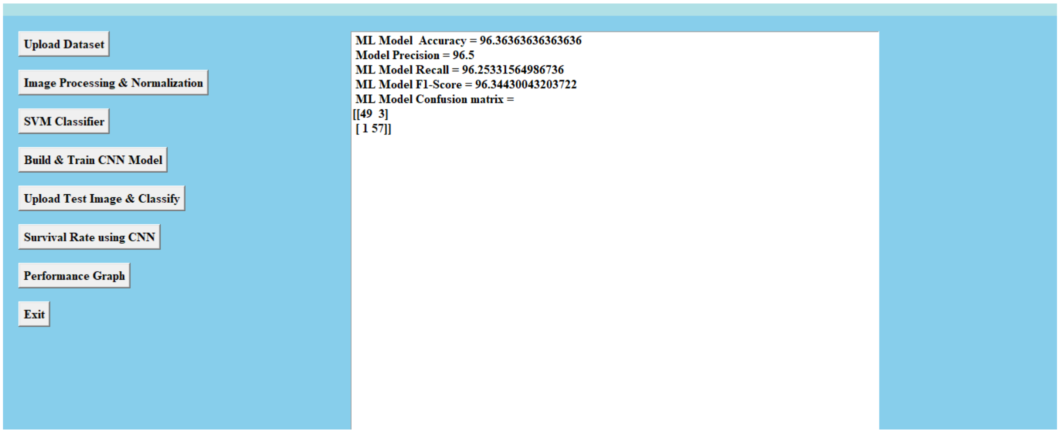


Figure 7: Performance of Support vector classifier

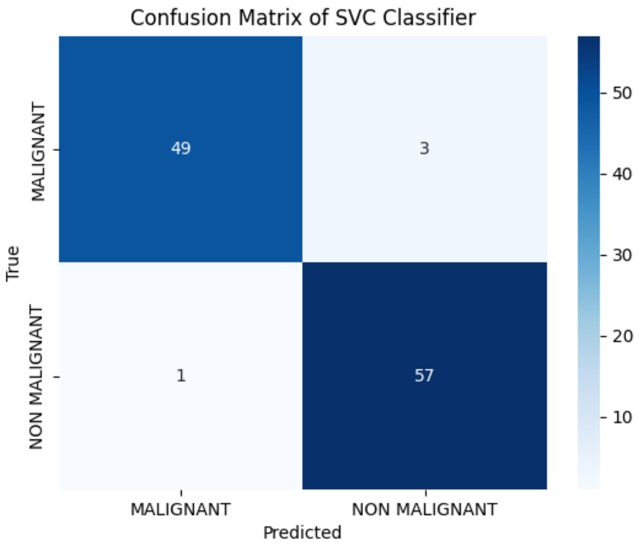


Figure 8: Confusion matrix of SVM Classifier

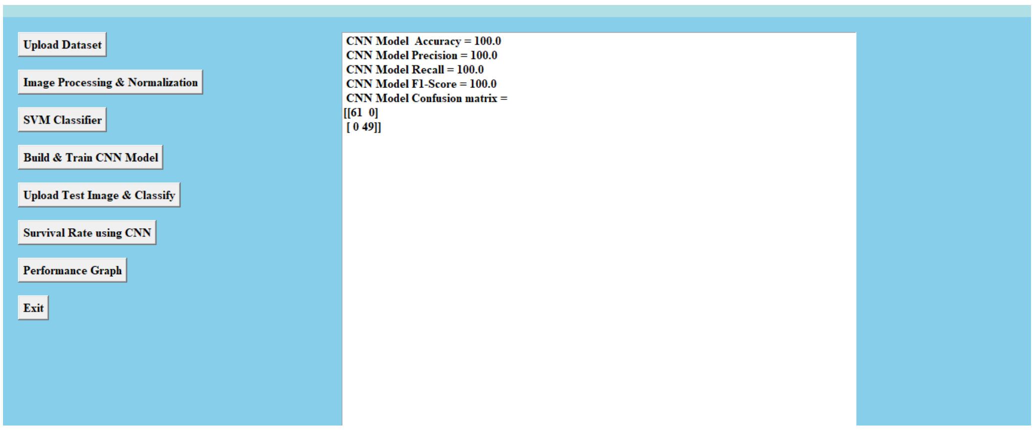


Figure 9: Performance evaluation of CNN Classifier.

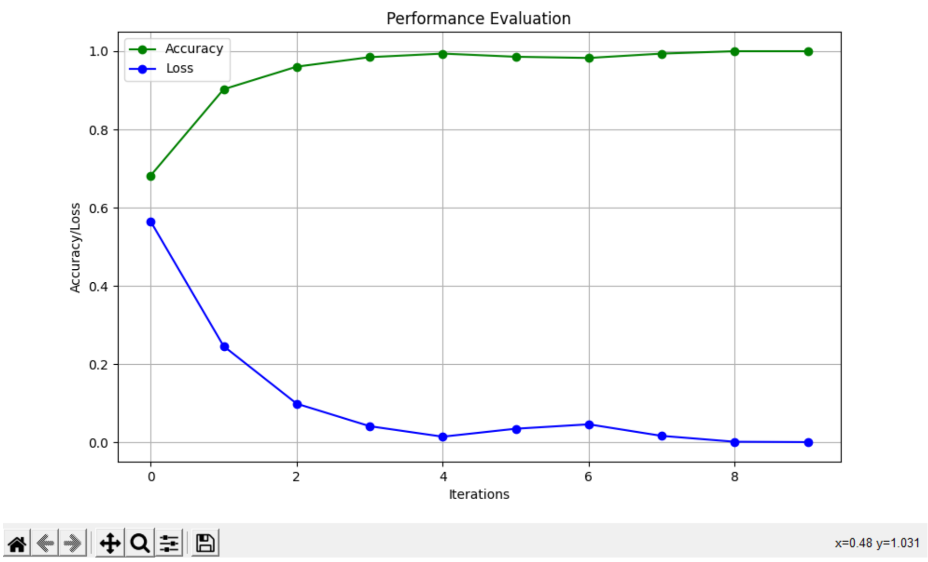


Figure 10: Iteration wise accuracy and loss graph

Figure 9 Showcases a graphical representation of the performance evaluation metrics associated with a Convolutional Neural Network (CNN) Classifier deployed for lung cancer detection. This visual display highlights the CNN model's effectiveness in accurately identifying lung cancer instances within images. Figure 10 shows Displays an iteration-wise graphical representation of the accuracy and loss values observed during the training process of the CNN Classifier. This graph offers insights into the model's learning progress and convergence towards optimal performance over successive training iterations. Figure 11 shows Portrays the visual depiction of the confusion matrix corresponding to the proposed CNN Model's performance evaluation. This confusion matrix furnishes detailed insights into the CNN model's classification accuracy and error rates across different classes.

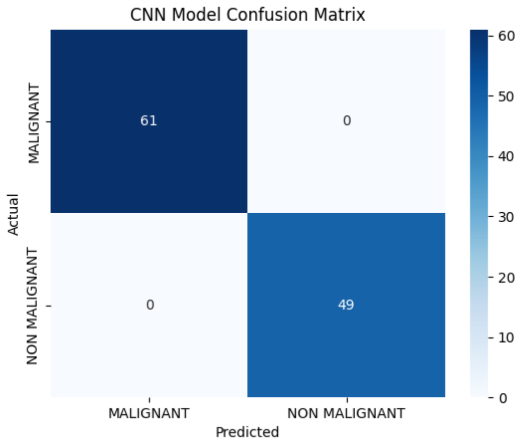


Figure 11: Confusion matrix of Proposed CNN Model

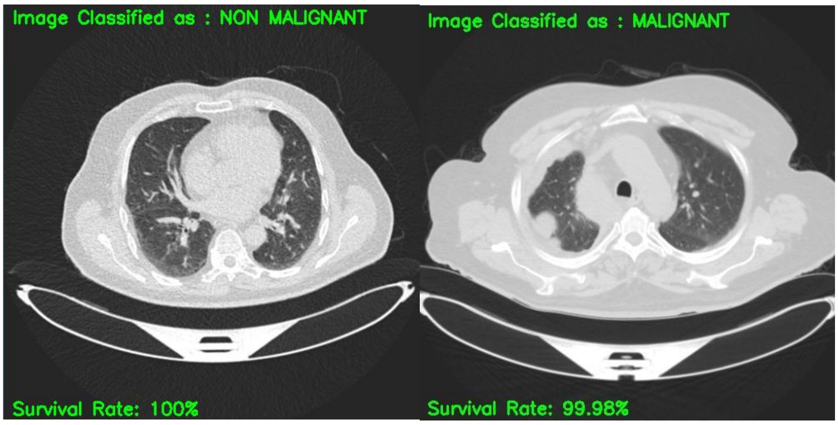


Figure 12: Prediction of survival rate and Prediction of output using CNN Model

Figure 12 Showcases the visual output generated by the CNN model, encompassing the predicted outcomes of lung cancer detection on a set of input images. This display likely includes examples of correctly and incorrectly classified lung tissue images. Figure 13 shows Consists of two distinct visual components; one representing the predictive estimation of survival rates based on detected lung cancer instances, and the other presenting the general output generated by the CNN Model. These visual outputs provide valuable insights into the prognostic capabilities and overall performance of the CNN model. Figure 18 shows that Presents a comparative graphical analysis between the performance metrics of the Gaussian Naïve Bayes (GNB) Classifier and the CNN Model. This comparative graph facilitates a comprehensive evaluation of the two models' respective effectiveness in lung cancer detection tasks

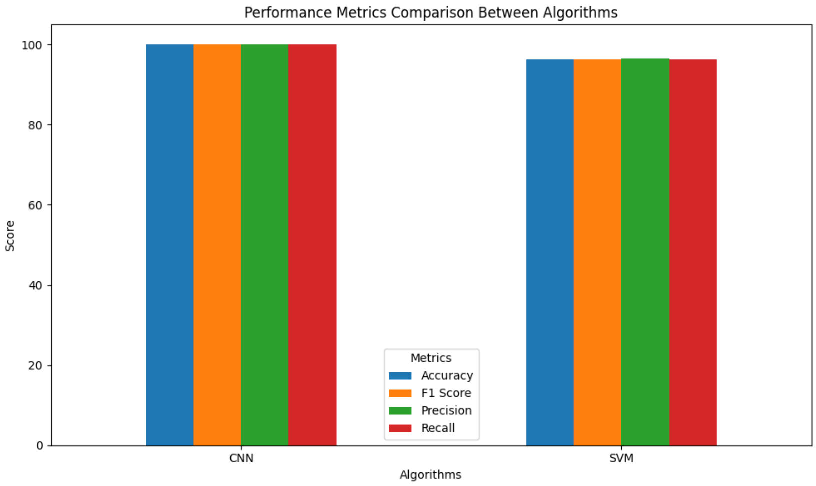


Figure 13: Performance Comparison graph of GNB Classifier and CNN Model.

## 5. CONCLUSION

In conclusion, the implementation of advanced modifications in convolutional neural network (CNN) models for the detection of lung cancer from chest scan images represents a significant advancement in early-stage diagnosis and monitoring of lung cancer. The proposed CNN model exhibits superior performance in classifying benign and malignant cases, distinguishing between normal and cancerous conditions with higher accuracy compared to conventional machine learning approaches like support vector machine (SVM) classifiers. By harnessing the power of deep learning, clinicians can benefit from more accurate and efficient detection and classification of lung nodules, enabling earlier intervention and better patient outcomes. The incorporation of deep learning-based medical imaging tools into clinical practice enhances diagnostic capabilities and supports medical professionals in making informed decisions for patient care.

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