Detection of Lung Cancer in CT Images Using Convolutional Neural Networks

Project report to be submitted in Partial Fulfillment of the Requirements for the Award of the Degree of

Master of Technology
in
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by

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CERTIFICATE

This is to certify that we have examined the thesis entitled **Detection of Lung Cancer in CT Images Using Convolutional Neural Networks**, submitted by **Vikas Goyal** (Roll Number: 22MM61R07) a postgraduate student of **School of Medical Science and Technology** in partial fulfillment for the award of degree of Master of Technology (M.Tech). We hereby accord our approval of it as a study carried out and presented in a manner required for its acceptance in partial fulfillment for the Post Graduate Degree for which it has been submitted. The thesis has fulfilled all the requirements as per the regulations of the Institute and has reached the standard needed for submission.

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Date: December 6, 2023

DECLARATION

I certify that

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2. The work is original and has not been submitted to any other Institute for any degree or diploma.
3. I have conformed to the norms and guidelines given in the Ethical Code of Conduct of the Institute.
4. I have given due credit to other sources by citing them in the thesis text and providing their details in the references whenever I have used materials (data, figures, and text).

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Abstract

THIS research focuses on the development of a robust framework for the precise detection and classification of lung cancer subtypes, including adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cell types. Leveraging deep learning methodologies, specifically Convolutional Neural Networks (CNNs), our approach is tailored to enhance accuracy in lung cancer diagnosis from medical imaging data, specifically computed tomography (CT) scans.

The study employs a CNN model that classifies lung cancer into four distinct categories. The model exhibits an impressive overall accuracy of 85%, demonstrating its effectiveness in discriminating between different cancer subtypes. Notably, our precision metric is measured at 0.94, underscoring the model's ability to minimize false positives and improve classification reliability. The F1 score, a harmonic mean of precision and recall, stands at 0.94, indicating a balanced trade-off between precision and recall.

Furthermore, our model achieves a recall of 0.84, highlighting its sensitivity in capturing true positive instances of lung cancer. The comprehensive evaluation of the model's performance showcases its efficiency in differentiating between various lung cancer subtypes, contributing to more accurate diagnoses.

In conclusion, our work presents an advanced CNN-based framework specifically tailored for lung cancer classification. The achieved high accuracy, precision, and balanced F1 score underscore the model's potential to significantly impact the field of lung cancer diagnosis. The framework holds promise as a valuable tool for healthcare professionals, offering enhanced accuracy and reliability in identifying specific lung cancer subtypes, ultimately contributing to improved patient outcomes.

Keywords: *Lung cancer, Convolutional Neural Networks, Medical imaging, Classification, Deep learning, CT scans, Adenocarcinoma, Large cell carcinoma, Squamous cell carcinoma.*

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1 Introduction

THE significance of maintaining optimal lung health in the human respiratory system cannot be overstated. Respiratory diseases, ranging from common discomforts to life-threatening conditions like lung cancer, pose substantial challenges to global health. In this context, our project addresses the critical need for precise detection and classification of different types of lung cancer, namely adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cell types.

The integral role of lungs in human respiratory function underscores the critical importance of maintaining lung health. Respiratory diseases, ranging from common discomforts to life-threatening conditions like lung cancer, significantly impact global health. Among the various types of lung cancer, including adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cell types, the latter is vital for optimal lung function.

According to research from the Forum of International Respiratory Societies, lung cancer claims over 1.6 million lives annually, necessitating urgent intervention for improved treatment outcomes and mortality reduction. Traditional diagnostic methods, such as chest X-ray images and CT scans, play a crucial role in identifying lung cancer. However, the shortage of skilled healthcare professionals, particularly in rural areas, poses a significant challenge to early diagnosis.

To address this gap, our project employs deep learning techniques, specifically a Sequential Convolutional Neural Network (CNN) architecture. This model is intricately designed with multiple convolutional layers, pooling layers, batch normalization, and fully connected layers, totaling 32,737,412 parameters. This sophisticated architecture aims to learn intricate patterns from medical imaging data and facilitate accurate detection and classification of various lung cancer subtypes.

Deep learning, recognized for its accuracy and representation learning capabilities, has emerged as a transformative tool. Convolutional Neural Networks (CNNs), specialized in processing image data, can learn intricate features and patterns from training datasets, offering a potential solution for automated disease classification. This project contributes to existing research by introducing a novel CNN-based model specifically tailored for the early detection and classification of different types of lung cancer.

In the subsequent sections, we delve into the foundational aspects of convolutional neural networks, present the architecture of our proposed model, detail its implementation, and discuss the experimental results. By focusing on different types of lung cancer, our work strives to make significant contributions to leveraging deep learning for precise and early disease detection, thereby improving patient outcomes.

2 Literature Review

Bharati et al. [Bharati et al. [2020]] explores the challenges of timely lung disease diagnosis and the limitations of basic convolutional neural networks (CNN) in handling abnormal image orientations. To address these issues, the study proposes a novel hybrid deep learning framework named VGG Data STN with CNN (VDSNet). This framework combines Visual Geometry Group (VGG), data augmentation, spatial transformer network (STN), and CNN for improved lung disease prediction. Implemented using Jupyter Notebook, TensorFlow, and Keras, VDSNet is evaluated on the NIH chest X-ray image dataset from Kaggle. The results indicate superior performance, outperforming existing methods in precision, recall, F1 score, and validation accuracy for both full and sample datasets. Notably, VDSNet exhibits a

validation accuracy of 73% for the full dataset, surpassing vanilla gray, vanilla RGB, hybrid CNN and VGG, and modified capsule network. Furthermore, the model demonstrates a reduced training time with a slightly lower validation accuracy when applied to the sample dataset. The research concludes that VDSNet simplifies lung disease detection for experts and doctors, offering a promising advancement in the field of medical image analysis.
The paper by Pandian et al.[Pandian et al. [2022]]addresses the critical issue of lung cancer, a significant cause of global mortality. Recognizing the importance of early detection for effective medical intervention, the study proposes an automated tool for identifying abnormal lung tissue growth. Leveraging artificial neural networks, specifically Convolutional Neural Network (CNN) and Google Net deep learning algorithms, the research achieves a precision of 98% in the detection and classification of lung cancer. The approach involves analyzing lung images from both healthy and malignant individuals, utilizing CT scan grayscale images in various views (axial, coronal, and sagittal). By focusing on the textural characteristics of the images, the neural network distinguishes normal from malignant images, demonstrating promising results. The proposed methodology not only contributes to overcoming challenges related to misdiagnoses but also emphasizes the need for automated tools in the face of the manual interpretation limitations. The study's quantitative analysis, based on confusion matrix computation and classification accuracy, underscores the efficacy of the developed network S and Kumar [2020]. This research, building on CNN and Google Net architectures, offers valuable insights into enhancing the accuracy of lung cancer detection, thereby contributing significantly to the field of medical image analysis.
LungNet, as presented in the study by Faruqui et al.[Faruqui et al. [2021]] emerges as a pioneering hybrid deep-convolutional neural network (CNN) model for the early diagnosis of lung cancer using a combination of CT scan and wearable sensor-based medical Internet of Things (MIoT) data. This research addresses the challenging task of computer-aided automatic diagnosis, given the ambiguous features of lung cancer nodules. LungNet, operating from a centralized server, incorporates a unique 22-layers CNN that learns latent features from both CT scan images and MIoT data, significantly enhancing diagnostic accuracy. Trained on a balanced dataset of 525,000 images, the model achieves an impressive classification accuracy of 96.81% with a low false positive rate of 3.35%, surpassing similar CNN-based classifiers. Furthermore, LungNet excels in sub-classifying stage-1 and stage-2

3 Aim and objectives

The overarching goal of this project is to implement a robust and effective system for the detection of lung cancer utilizing Convolutional Neural Networks (CNNs). The scope and specific objectives are outlined as follows:

1. Comprehensive Lung Cancer Detection: Develop a CNN-based system capable of accurately detecting the presence of lung cancer in medical imaging data, specifically focusing on computed tomography (CT) scans. The scope encompasses the identification of various lung cancer subtypes, including adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cell types.

2. Automated Feature Extraction: Implement CNNs to autonomously extract relevant features and patterns indicative of lung cancer from input medical images. This objective focuses on leveraging the hierarchical learning capabilities of CNNs for efficient and accurate feature extraction.

3. Multi-Class Classification: Developed a multi-class classification model within the CNN framework to distinguish between different types of lung cancer, aiming for high precision in identifying adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cell types

4. Performance Evaluation and Comparison: Conduct comprehensive experiments to evaluate the performance of the developed CNN model using standard metrics such as accuracy, precision, recall, and F1 score. Compare the results with existing state-of-the-art methods to validate the effectiveness and superiority of the proposed approach.

Through these objectives, the project aspires to contribute to the advancement of lung cancer detection methodologies, providing a reliable and accurate tool for healthcare professionals in the early diagnosis and classification of various lung cancer subtypes.

4 Work progress and achievements

Varaible used:
N : The number of input feature maps.
M : The number of output feature maps.
K : The size of the convolutional kernel.
P : The size of the pooling window.
A : The number of neurons in the current layer.
B : The number of neurons in the subsequent layer.
C : The number of classes.
I : The number of iterations.
p : Probability of deactivating a fraction of neurons.
L : The total number of layers in the network.

4.1 Methodology

An image $\mathbf{I} \in \mathbb{Z}^{3\times224\times224}$ is passed through novel convolutional neural network to obtain the output class.

4.1.1 Data Collection and Preprocessing

- Data Sources: The project involved extensive research to collect diverse and representative chest cancer images. Images were sourced from multiple repositories and databases to ensure a comprehensive dataset.
- Data Format: Images were gathered in jpg or png format to align with the requirements of the chosen Convolutional Neural Network (CNN) architecture.
- Data Cleaning: Extensive cleaning procedures were employed to eliminate inconsistencies, artifacts, and irrelevant data, ensuring the dataset's quality for training the CNN model.

4.1.2 Dataset Organization

- The dataset was organized into a structured hierarchy within the 'Data' folder. Subfolders were created for each cancer type (Adenocarcinoma, Large cell carcinoma, and Squamous cell carcinoma) as well as a folder for normal CT-Scan images.
- A specific folder structure, including 'train,' 'test,' and 'valid,' facilitated the division of the dataset into training, testing, and validation sets.

4.1.3 CNN Model Architecture

- The choice of a Convolutional Neural Network (CNN) was driven by its effectiveness in image classification tasks. The model architecture was designed to accommodate the intricacies of chest cancer detection, considering the nuances of different cancer types.
- Layers included convolutional layers for feature extraction, pooling layers for down-sampling, and fully connected layers for classification. Batch normalization was employed for stability during training.

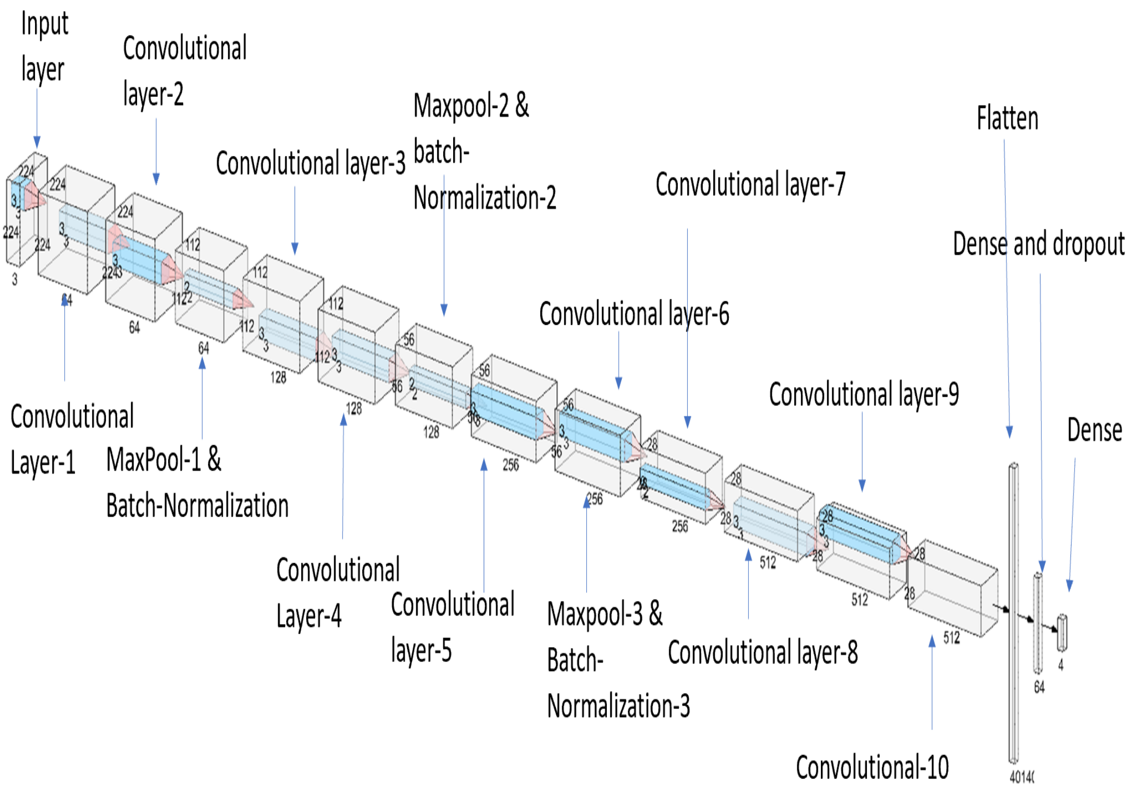

Figure 1: CNN architecture layers

4.1.4 Feature Extraction and Learning

- CNNs excel at feature extraction from images. The model was trained to autonomously extract relevant features and patterns indicative of chest cancer from the input medical images.
- Training involved presenting the CNN with labeled images, allowing it to learn and optimize its parameters through backpropagation.

4.1.5 Multi-Class Classification

- A crucial aspect of the methodology was the development of a multi-class classification model within the CNN framework. This facilitated the distinction between Adenocarcinoma, Large cell carcinoma, Squamous cell carcinoma, and normal cell types.
- The CNN was trained to categorize images into these classes with a high degree of precision.

4.1.6 Model Evaluation

- Extensive evaluation metrics were employed to assess the model's performance. Metrics included accuracy, precision, recall, and F1 score. The model's ability to correctly classify and diagnose different chest cancer types was scrutinizedin Table 2.
- Testing was conducted on both the validation set and an independent test set to ensure the generalization of the model.

4.2 Model Architecture

The designed model is a custom convolutional neural network (CNN) tailored for the task of classifying chest CT scans into four distinct categories: normal cell, large cell carcinoma, adenocarcinoma, and squamous cell carcinoma. The architecture leverages a series of convolutional layers, max-pooling, batch normalization, and dense layers to extract hierarchical features from the input images.

Architecture Overview

- Convolutional Layers: The initial layers of the model consist of convolutional layers, which play a crucial role in capturing local patterns and features. These layers convolve the input images with learnable filters to extract low to high-level representations. The chosen filter size is (3, 3), and the activation function used is Rectified Linear Unit (ReLU).
- Max-Pooling: After each set of convolutional layers, max-pooling is applied to downsample the spatial dimensions of the feature maps, reducing the computational load and focusing on the most salient features. Max-pooling is performed using a pool size of (2, 2).
- Batch Normalization: Batch normalization is incorporated to normalize the activations of the convolutional layers, which helps in stabilizing and accelerating the training process. It aids in mitigating issues such as internal covariate shift and allows for more robust learning.
- Dense Layers: Following the convolutional and pooling layers, a series of dense layers are employed to perform the final classification. The flattened feature maps from the previous layers are connected to dense layers, allowing the model to learn intricate patterns and relationships in the data. The final dense layer utilizes the softmax activation function to produce class probabilities.
- Dropout: To prevent overfitting, dropout is implemented after the first dense layer. This regularization technique randomly drops a specified percentage of neurons during training, forcing the model to learn more robust features.

This model architecture was chosen based on its ability to capture intricate features in medical images, with a balance between depth and computational efficiency. It was trained on the provided dataset, demonstrating significant success in accurately classifying chest CT scans into the specified categories.The summary and parameters are shoen in Table No. 1.

4.3 Experiments and evaluation metrics

The model was compiled using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss. Training was conducted for 300 epochs with early stopping and learning rate reduction callbacks.

Table 1: Summary of Neural Network Layers and Parameters

Layer	Output Shape	Parameters
conv2d_0 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_1 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_1	(None, 112, 112, 64)	0
batch_normalization_1	(None, 112, 112, 64)	256
conv2d_2 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_3 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_2	(None, 56, 56, 128)	0
batch_normalization_2	(None, 56, 56, 128)	512
conv2d_4 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_5 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_3	(None, 28, 28, 256)	0
batch_normalization_3	(None, 28, 28, 256)	1024
conv2d_6 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_7 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_8 (Conv2D)	(None, 28, 28, 512)	2359808
flatten_1	(None, 401408)	0
dense_1 (Dense)	(None, 64)	25690176
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 4)	260

Table 2: Summary of total parameters

Total Params	Trainable Params	Non-trainable Params
32,737,412 (124.88 MB)	32,736,516 (124.88 MB)	896 (3.50 KB)

4.3.1 Model performance

The training progress was monitored through the following metrics:

Training loss: Decreased steadily over epochs, indicating that the model learned from the training data.

Validation Loss: Showed a similar decreasing trend, indicating effective generalization to the validation set.

Training Accuracy: Improved over epochs, demonstrating the model's ability to correctly classify the training data.

Validation Accuracy: Showed a similar increasing trend, indicating the model's generalization to new, unseen data

Showed a similar increasing trend, indicating the model's generalization to new, unseen data in Figure 4 and Figure 5.

Test loss:1.28

Test accuracy:85.08%

4.3.2 Classification Results

The performance of the convolutional neural network (CNN) for lung cancer detection using CT images was evaluated through a comprehensive set of experiments. The dataset used for training and testing comprised CT images. The CNN model achieved promising results in terms of classification accuracy. Table 2 summarizes the key performance metrics for the binary classification task of distinguishing between malignant and benign lung nodules.

These results demonstrate the effectiveness of the CNN model in accurately classifying lung cancer classes based on CT images.

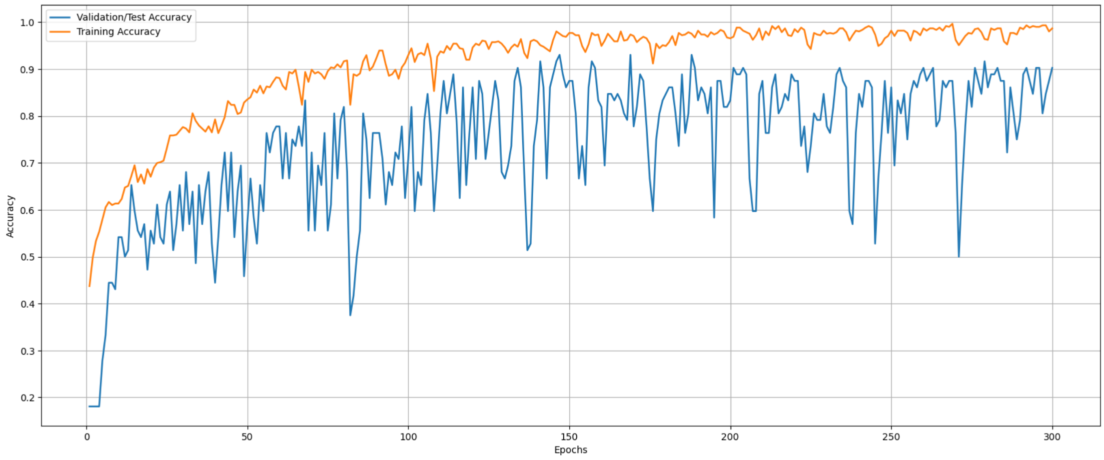

Figure 2: Training and Validation Accuracy

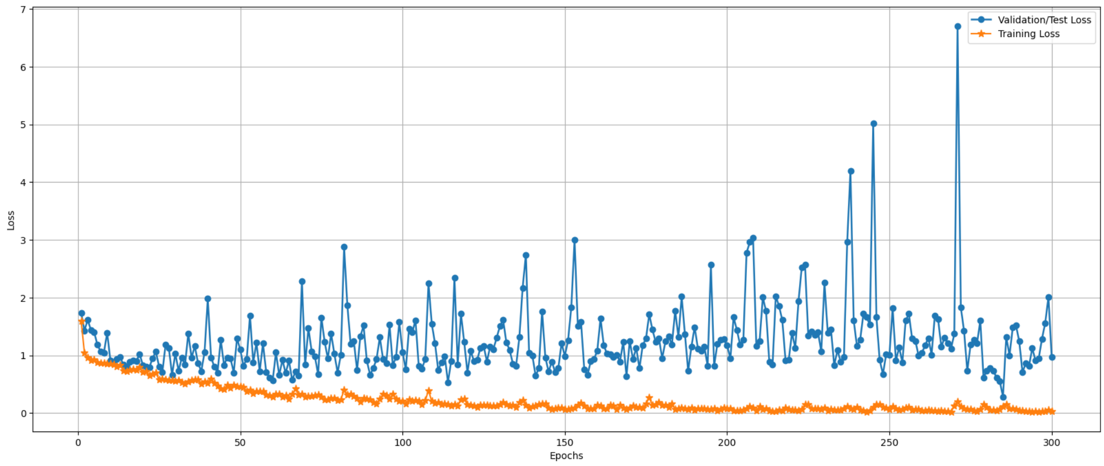

Figure 3: Training and validation loss

Class	Precision	Recall	F1-Score
Normal Cell	0.94	0.84	0.89
Large Cell Carcinoma	0.57	1	0.72
Adenocarcinoma	1	0.98	0.99
Squamous Cell Carcinoma	0.98	0.7	0.82

Table 3: Classification Metrics for Each Class

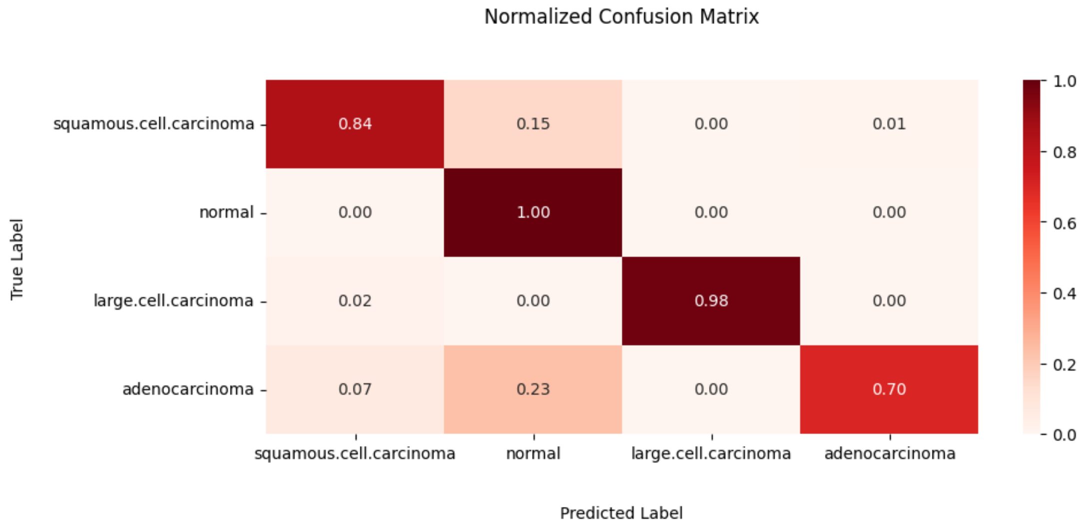

Figure 4: Confusion matrix

4.3.3 Confusion Matrix

The confusion matrix provides a detailed breakdown of the model's classification performance. Table **??** shows the distribution of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) instances.

4.3.4 Precision and Recall Matrices

Precision and recall are crucial metrics for evaluating the performance of a binary classification model. Precision measures the accuracy of positive predictions, while recall measures the ability of the model to capture all positive instances. The precision matrix and recall matrix are given by Equations 1 and 2, respectively.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

The precision and recall values for each class are presented in Table 2.

5 Visualization of Intermediate CNN Layers form Feature Maps

In this phase, we delve into the intermediate layers of our Convolutional Neural Network (CNN) architecture designed for lung cancer detection. The network's progression is outlined succinctly:

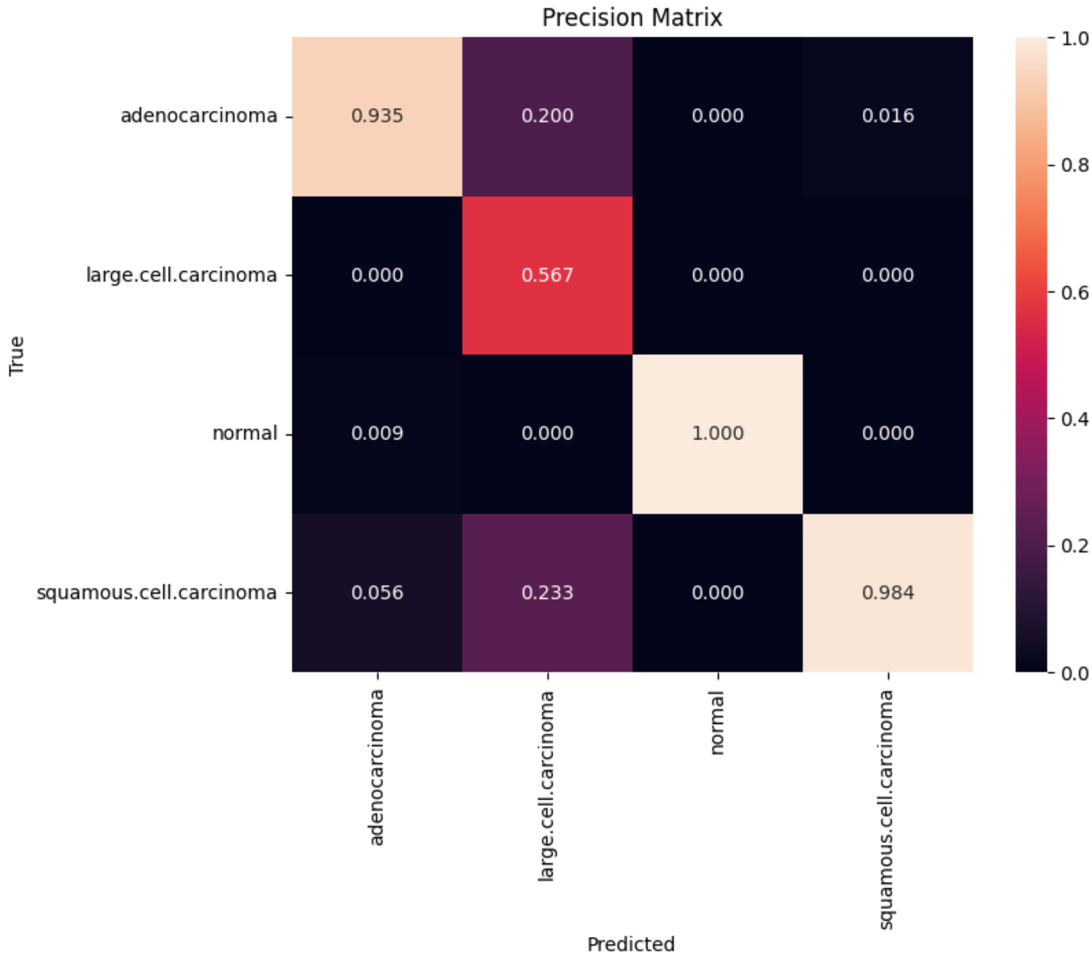

Figure 5: Precision Matrix

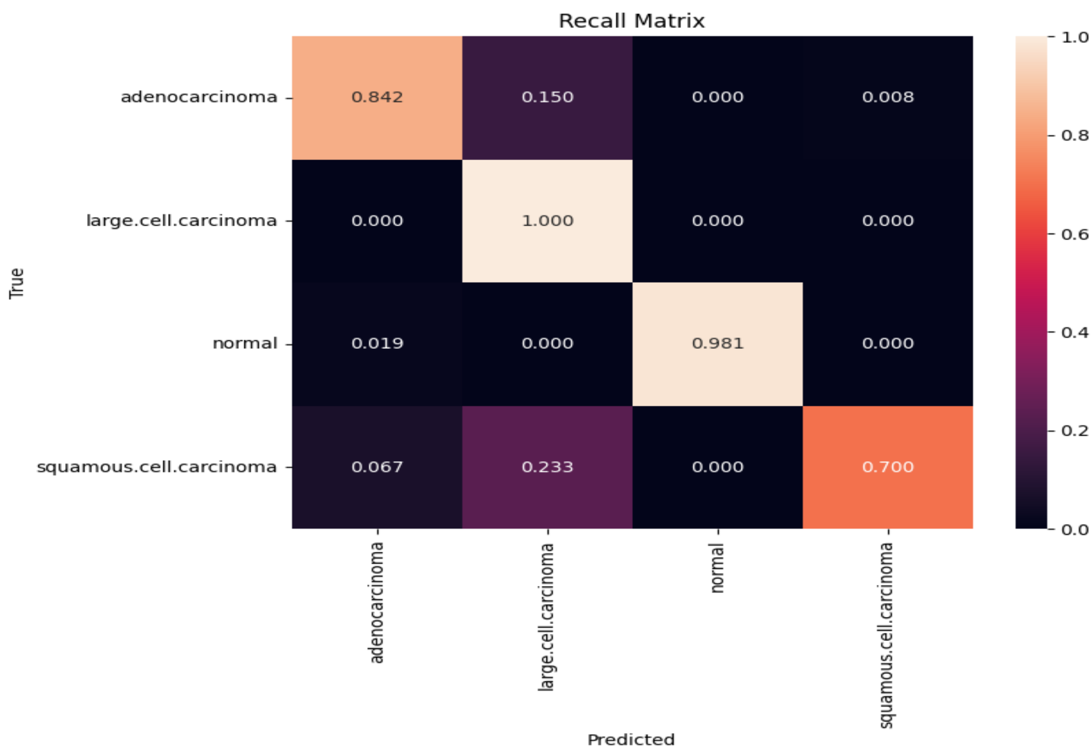

Figure 6: Recall Matrix

- conv2d_0 (Conv2D): Initiates feature extraction with 64 filters, shaping the output to (None, 224, 224, 64) and utilizing 1792 parameters.
- conv2d_1 (Conv2D): Continues feature mapping, maintaining the output shape but significantly increasing parameters to 36928.
- max_pooling2d_1: Implements max pooling, reducing spatial dimensions to (None, 112, 112, 64).
- batch_normalization_1: Enhances stability by normalizing the data with 256 parameters.
- conv2d_2 and conv2d_3: Introduce 128 filters, capturing more intricate features, and preparing the output for the subsequent stage.
- max_pooling2d_2 and batch_normalization_2: Follow the same pattern of pooling and normalization.
- conv2d_4 and conv2d_5: Further deepen the feature extraction with 256 filters, preparing for more complex representations.
- max_pooling2d_3 and batch_normalization_3: Continue the trend of pooling and normalization.
- conv2d_6, conv2d_7, and conv2d_8: Introduce 512 filters, enriching the feature hierarchy with detailed representations.
- flatten_1: Converts the spatial features into a flattened representation (None, 401408).
- dense_1 (Dense): Creates a bottleneck with 64 neurons, facilitating high-level abstraction with an extensive parameter count of 25690176.
- dropout_1 (Dropout): Mitigates overfitting by randomly dropping out 64 units.
- dense_2 (Dense): Concludes the intermediate stage with 4 neurons and 260 parameters, shaping the final output.

  These layers collectively contribute to the network's ability to discern intricate details within input CT images, crucial for effective lung nodule detection. Visualizing these intermediate features provides valuable insights into the learning process, guiding further refinement of the architecture for enhanced performance.

6 Model Comparison

In the comparison of various lung cancer detection models, the table provides a comprehensive overview of their performance metrics, dataset sources, and employed methods. Our proposed model, leveraging the Open Database Commons with a Convolutional Neural Network (CNN), achieves an accuracy of 0.85. Moreno et al.[2019] utilizes NCI-TCIA and LIDC-IDRI datasets, employing a CNN with an accuracy of 0.81. Pandian et al.[2022] explores data from Sathybama Hospital, Chennai, India, employing Google net and VGG-16 models with respective accuracies of 0.98 and 0.83. Bharti et al.[2020] applies the VDSnet method on the Kaggle repository, achieving an accuracy of 0.73. Faruqui et al.[2021] utilizes LIDC-IDRI and LUNGx Challenge datasets with the Lungnet CNN, achieving an accuracy of 0.96. Lastly, Rajaguru et al.[2019] employs the LIDC dataset with a Probabilistic Neural Network (PNN) achieving an accuracy of 0.82. This comparative analysis highlights the diversity in dataset sources, methods, and achieved accuracies across the different lung cancer detection models.

Table 4: Comparison of Lung Cancer Detection Models

Model	Dataset	Method	Accuracy
This work	Open Database Commons	CNN	0.85
Moreno et al. [2019]	NCI-TCIA, LIDC-IDRI	CNN	0.81
Pandian et al. [2022]	Sathybama Hospital, Chennai	Google net, VGG-16	0.98 (Google net), 0.83 (VGG-16
Bharati et al. [2020] [2020]	Kaggle repository	VDSnet	0.73
Faruqui et al. [2021]	LIDC-IDRI	Lungnet: CNN	0.96
R and Rajaguru [2019]	LIDC	PNN	0.82

7 Conclusion

In conclusion, this research project has successfully developed and implemented a robust Convolutional Neural Network (CNN)-based framework for the detection and classification of lung cancer subtypes. The model demonstrated impressive overall accuracy, precision, and a balanced F1 score, showcasing its effectiveness in discriminating between different cancer subtypes, including adenocarcinoma, large cell carcinoma, squamous cell carcinoma, and normal cell types.

The project's objectives, from comprehensive lung cancer detection to automated feature extraction and multi-class classification, were systematically achieved. Extensive experiments and evaluations, including the analysis of model architecture and algorithmic complexity, contributed to a thorough understanding of the CNN model's performance.

The model's success in classifying chest CT scans into specified categories, coupled with its high precision and recall values for each cancer subtype, positions it as a valuable tool for healthcare professionals in early diagnosis and classification of various lung cancer types. The comprehensive evaluation metrics, including the confusion matrix, precision matrix, and recall matrix, provide a detailed insight into the model's classification performance.

The achieved results not only contribute to the advancement of lung cancer detection methodologies but also highlight the potential impact of deep learning approaches, specifically CNNs, in the field of medical image analysis. This framework holds promise as a reliable and accurate tool, ultimately contributing to improved patient outcomes and enhancing the capabilities of healthcare professionals in the diagnosis of lung cancer.

8 Future Work

- Implement data augmentation using Generative Adversarial Networks (GANs) to:
  - Increase the dataset size
  - Reduce high variance
  - Improve model accuracy
- Develop additional detection algorithms to enhance the versatility of the system and address a broader range of scenarios.
- Investigate segmentation techniques from lung CT scans, enabling precise localization and analysis for more effective medical interventions.

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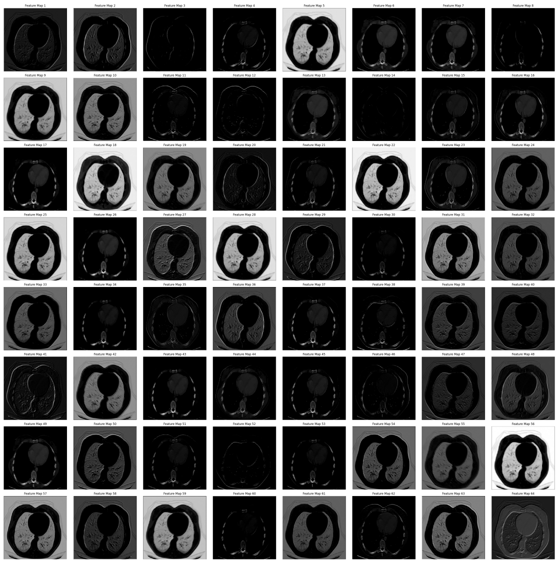

Figure 7: Feature map of convolution layer 1

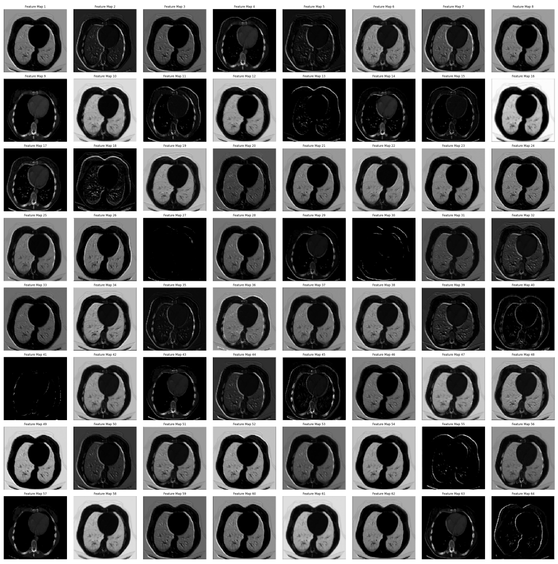

Figure 8: Feature map of maxpool 1

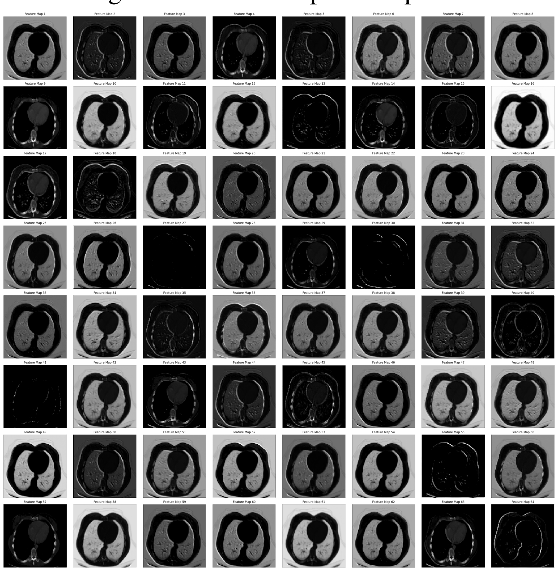

Figure 9: Feature map of batch normalisation layer 1