Industry Oriented Mini Project Report
on

Lung Nodule Detection Using Deep Learning Techniques

Submitted in partial fulfillment of the requirements
for the award of degree of

BACHELOR OF TECHNOLOGY
in
Information Technology
by

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(NAAC 'A' Grade & NBA Accredited- ECE, EEE, CSE & IT)
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CERTIFICATE

This is to certify that the Project report on **"Lung Nodule Detection Using Deep Learning Techniques"** is a bonafide work carried out by **G. Ravi Sri Chandana (20WH1A1215), V. Jaswitha (20WH1A1224)** and **P. Sai Varshitha (21WH5A1204)** in the partial fulfillment for the award of B.Tech degree in **Information Technology , BVRIT HYDERABAD College of Engineering for Women, Bachupally, Hyderabad** affiliated to Jawaharlal Nehru Technological University, Hyderabad, under my guidance and supervision. The results embodied in the project work have not been submitted to any other university or institute for the award of any degree or diploma.

Internal Guide	**Head of the Department**
Dr.P Kayal	**Dr. Aruna Rao S L**
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DECLARATION

We hereby declare that the work presented in this project entitled **"Lung Nodule Detection Using Deep Learning Techniques"** submitted towards completion of in IV year I sem of B.Tech IT at "BVRIT HYDERABAD College of Engineering for Women",Hyderabd is an authentic record of our original work carried out under the esteemed guidance of **Dr. P. Kayal, Associate Professor**, Department of Information Technology.

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ABSTRACT

Lung nodules are small, rounded or oval growths within the lungs which are typically detectable through chest X-rays or CT scans. They can arise from various causes, encompassing both benign and malignant origins. Benign nodules may be attributed to infections, inflammation, or lung tissue scarring, while malignant ones could signal the presence of lung cancer. The primary objective of this project is to develop a machine learning model tailored to automate the identification and categorization of lung nodules within medical images. This initiative seeks to enhance early lung cancer detection and reduce the workload of radiologists. The workflow encompasses data collection, model development, and rigorous training. The model's efficacy is subsequently evaluated utilizing relevant metrics, with the results presented alongside insightful observations and potential implications for advancements in healthcare and medical research within the domain. This endeavor represents a significant stride toward bolstering diagnostic capabilities in the medical field.

Keywords: CT scans, Lung cancer, Machine learning

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Chapter 1

Introduction

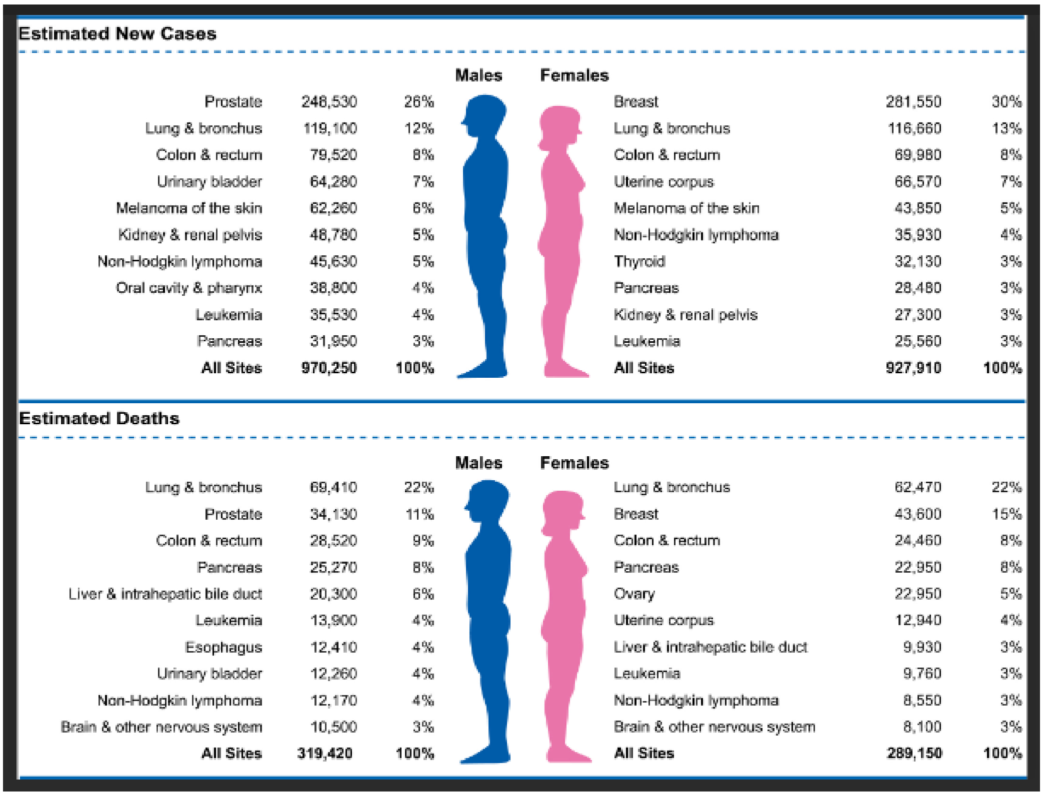
Lung cancer poses a substantial threat due to its high fatality rates and prevalence, causing 1.8 million global deaths [4]. The rise in smaller pulmonary nodules, spanning 0-3mm, signifies a noteworthy trend deserving attention worldwide. These minute nodules often serve as early signals for potential lung cancer, progressing into larger tumors with complex manifestations. Early detection and prompt intervention are pivotal in improving prognoses for individuals with these nodules. Lung CT scanning, crucial for early diagnosis, provides precise cross-sectional views aiding in nodule identification within normal anatomical structures [1]. While CT scans excel in detecting and characterizing these nodules with minimal risk, other methods like X-rays lack adequate sensitivity, and MRI scans, though adept at visualizing soft tissues, have limited utility in lung imaging. Radiologists face challenges in interpreting numerous CT images swiftly, leading to substantial workload and subjective diagnostic discrepancies. Approaches integrating nodule characteristics and patient data, like the Mayo Clinic model, enhance diagnostic efficiency but demand significant manual effort [2].

1.1 Motivation

The motivation behind this project stems from the alarming rise in lung cancer cases and the significant impact it has on both male and female populations[3]. As shown in figure 1.1, with approximately 12% (117,910) new cases reported in males and 13% (118,830) new cases reported in females, lung cancer stands as one of the most prevalent and concerning forms of cancer globally [4]. Moreover, the devastating statistics continue with an estimated 21% (68,820) of deaths in males and 21% (61,360) of deaths in females attributed to lung cancer, surpassing the mortality rates of various other cancer types [5].

These distressing numbers highlight the urgent need for advanced and accurate methods to detect and diagnose lung cancer at its early stages. Early detection plays a pivotal role in improving patient outcomes and increasing the effectiveness of treatment strategies. However, the detection of smaller lung nodules, particularly those between 0-3mm in diameter, presents a significant challenge due to their subtle appearance in medical imaging data such as CT scans.

Hence, the project's primary motivation lies in leveraging cutting-edge technology, particularly deep learning and image analysis, to develop an automated system capable of detecting and categorizing these minute lung nodules as benign or malignant. By creating a reliable and efficient tool for nodule classification, the project aims to assist healthcare professionals in timely diagnosis, enabling swift intervention and personalized treatment plans, ultimately working towards reducing the mortality rate associated with lung cancer.



Estimated New Cases

Males			Females		
Prostate	248,530	26%	Breast	281,550	30%
Lung & bronchus	119,100	12%	Lung & bronchus	116,660	13%
Colon & rectum	79,520	8%	Colon & rectum	69,980	8%
Urinary bladder	64,280	7%	Uterine corpus	66,570	7%
Melanoma of the skin	62,260	6%	Melanoma of the skin	43,850	5%
Kidney & renal pelvis	48,780	5%	Non-Hodgkin lymphoma	35,930	4%
Non-Hodgkin lymphoma	45,630	5%	Thyroid	32,130	3%
Oral cavity & pharynx	38,800	4%	Pancreas	28,480	3%
Leukemia	35,530	4%	Kidney & renal pelvis	27,300	3%
Pancreas	31,950	3%	Leukemia	25,560	3%
All Sites	**970,250**	**100%**	**All Sites**	**927,910**	**100%**

Estimated Deaths

Males			Females		
Lung & bronchus	69,410	22%	Lung & bronchus	62,470	22%
Prostate	34,130	11%	Breast	43,600	15%
Colon & rectum	28,520	9%	Colon & rectum	24,460	8%
Pancreas	25,270	8%	Pancreas	22,950	8%
Liver & intrahepatic bile duct	20,300	6%	Ovary	22,950	5%
Leukemia	13,900	4%	Uterine corpus	12,940	4%
Esophagus	12,410	4%	Liver & intrahepatic bile duct	9,930	3%
Urinary bladder	12,260	4%	Leukemia	9,760	3%
Non-Hodgkin lymphoma	12,170	4%	Non-Hodgkin lymphoma	8,550	3%
Brain & other nervous system	10,500	3%	Brain & other nervous system	8,100	3%
All Sites	**319,420**	**100%**	**All Sites**	**289,150**	**100%**

Figure 1.1: World Cancer Statistics 2022
(Courtesy : allcancersymptoms.com/exploring-world-cancer-statistics-202)

1.2 Objective

The core objective of our project is to emphasize the critical significance of early detection and assessment of lung nodules ranging from 0-3mm. These minute nodules often act as vital indicators of potential lung cancer, escalating into larger tumors. The primary goal is to stress the pivotal role of lung computed tomography (CT) scanning in enabling the timely diagnosis of these small pulmonary abnormalities. CT scans offer detailed cross-sectional views that facilitate the identification of early-stage nodules while showcasing normal anatomical structures and any potential pathological indications. By advocating for the use of CT scans over conventional methods like X-rays or MRI scans, the objective underscores the superior efficacy of CT scans in detecting and characterizing these smaller nodules, emphasizing their importance in initiating timely treatment strategies. Also, it acknowledges the challenges faced by radiologists in interpreting numerous CT images swiftly, highlighting the need for improved diagnostic methodologies to ensure accurate and prompt identification of potential lung cancer at its early stages.

The objective aims to stress the critical need for improved diagnostic accuracy through enhanced methodologies, including the integration of pulmonary nodule characteristics from CT images. This objective emphasizes the ongoing efforts in the medical field to enhance diagnostic efficiency and accuracy in identifying potential lung cancer at its early stages, ultimately improving patient outcomes and prognosis.

1.3 Problem Definition

Accurate identification and classification of lung nodules within the 0-3mm size range from CT scan images remain a critical challenge in early lung cancer diagnosis. The aim of this study is to develop a robust deep learning-based system for automated classification of these small-sized nodules as either benign or malignant as shown in figure 1.2. Leveraging a dataset of annotated CT scan images containing these nodules, this research seeks to design and train a convolutional neural network (CNN) model capable of discerning subtle features indicative of nodule malignancy. By effectively differentiating between benign and malignant nodules, the proposed model aims to assist healthcare practitioners in making timely and accurate diagnostic decisions, thereby potentially enhancing patient outcomes through early intervention strategies.

This project's significance lies in bridging the gap in lung cancer diagnosis by creating an automated and precise system specifically tailored to identify 0-3mm lung nodules. The successful development of such a model holds the potential to revolutionize lung cancer detection protocols, offering radiologists a reliable tool to swiftly and accurately classify these small nodules as benign or malignant. By integrating this technology into clinical workflows, the ultimate objective is to enable healthcare providers to expedite diagnoses, provide targeted treatments, and ultimately improve patient care and outcomes in the realm of lung cancer management.

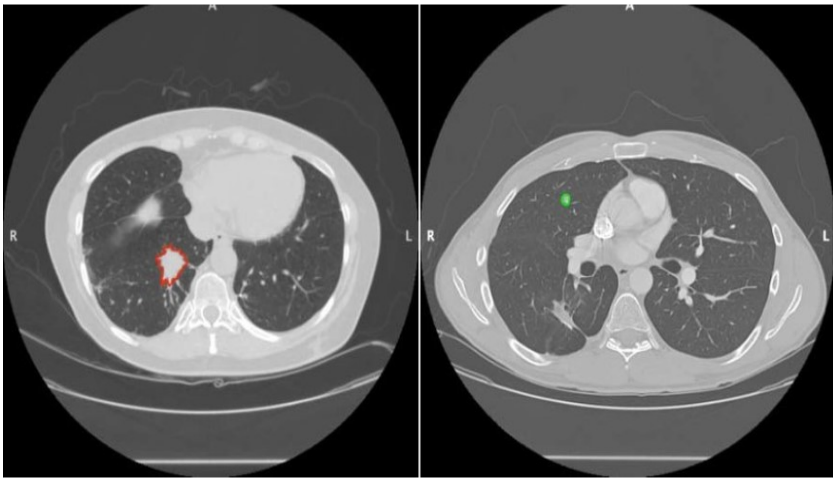


Figure 1.2: Malignant and Benign Lung Nodule
(Courtesy researchgate.net/publication/322975873)

Chapter 2

Literature Survey

The paper entitled as [6] discusses the criticality of early and precise diagnosis in pulmonary cancer, highlighting the potential for computer-aided diagnosis systems to augment radiologists' efficiency. It introduces a deep automated lung nodule diagnosis system, leveraging 3D-CNN, SVM with MKL algorithms, and clinical data to enhance diagnosis accuracy. Employing a 34-layer 3D-ResNet for image feature extraction, the system integrates heterogeneous features, demonstrating improved lung nodule diagnosis efficacy. However, due to limited clinical data and imbalance issues, directly determining feature significance remains challenging. The study emphasizes the need for exploring relationships between features and lung cancer, suggesting future improvements for a comprehensive automated nodule diagnosis system encompassing detection, clinical feature extraction, and classification to optimize radiologists' efficiency.

The publication titled as [7] addresses the challenges posed by nodule heterogeneity and complex surrounding environments, the research introduces a two-stage convolutional neural network (TSCNN) architecture. The initial stage employs an enhanced UNet segmentation network to identify potential nodules, while the subsequent stage utilizes a novel dual pooling structure within three 3D CNN classification networks to reduce false positives. Data augmentation via random mask-based methods and ensemble learning enhance model generalization. Experimentation on the LUNA dataset validates the proposed TSCNN's competitive detection performance, confirmed through ablation studies and comparative analysis against existing methods. The method demonstrates promising potential for accurate lung nodule detection, presenting a significant stride in early lung cancer diagnosis with 84.8% accuracy.

The paper entitled as [8] describes the significance of lung nodules in detecting lung cancer early, prompting the development of Computer-Aided Diagnosis (CAD) systems to aid radiologists in classifying malignancy from CT images. It introduces a novel approach using transferable texture Convolutional Neural Networks (CNN) equipped with an Energy Layer (EL) to enhance pulmonary nodule classification performance while reducing computational complexity. The proposed CNN architecture, incorporating EL for texture feature extraction, exhibits promising results with six-fold cross-validation achieving an accuracy of 85.86%±0.72% and an error rate of 3.30%±0.72% on LIDC-IDRI and the LUNGx Challenge databases. Additionally, the model's effectiveness is validated on the MNIST dataset, demonstrating state-of-the-art accuracy of 85.86% with a minimal error rate of 0.12%. The findings highlight the efficacy of the proposed texture CNN in classifying benign and malignant nodules without complex preprocessing, showcasing its potential for lung nodule malignancy classification tasks.

The publication titled as [9] focuses on classifying pulmonary nodules in CT images using fusion methods based on feature extraction and ensemble learning. The have utilized the LUNA16 dataset, which examines the attributes of nodules annotated by radiologists. Firstly, they extracted deep features from pre-trained DCNN models (AlexNet, VGG-16, VGG-19) and proposed fusion techniques like averaging prediction scores and ensemble methods, exploring SVM, LDA, and AdaBoostM2 classifiers' efficacy. Results highlight the superiority of ensemble learners based on MAX-VOTE in binary nodule classification and demonstrate promising multi-class classification performance with high accuracy and specificity scores, indicating improved pulmonary nodule classification accuracy.

The paper entitled as [10] focuses on lung cancer detection using chest CT scans. They introduced a new dataset called PN9, comprising 8,798 CT scans with 40,439 annotated nodules in nine classes, including solid, part-solid, ground-glass, and calcific nodules. Their approach, SANet, utilizes a slice grouped non-local module (SGNL) and a 3D region proposal network to detect pulmonary nodules accurately. They also developed a false positive reduction module (FPR) to reduce false alarms. Comparison with existing datasets like LUNA16 shows PN9's significant advantage in size and diversity, offering more potential for effective nodule detection and classification. This dataset can aid in identifying smaller nodules, allowing earlier diagnosis and treatment. Overall, PN9's size, diversity, and performance enhancements make it valuable for lung nodule research and diagnosis.

The publication titled as [11] focuses on detecting pulmonary nodules in chest X-rays, crucial for early lung cancer diagnosis. Using deep learning algorithms, they aim to improve nodule detection accuracy, which is challenging due to limited annotated data sets and class imbalances. The research compares various object detection models and strategies to address these challenges. They utilized diverse deep learning models like Faster-R-CNN, RetinaNet, EfcientDet-D2, and YoloV5, applying various techniques such as transfer learning, data augmentation, and model ensembling to achieve state-of-the-art performance in nodule detection from chest x-rays. Their approach involved a systematic analysis, leveraging multiple models, and addressing class imbalances and limited data sets, providing insights and a robust method for nodule detection in chest X-rays with 80% accuracy.

Chapter 3

System Design

3.1 Proposed System

This section presents the proposed lung cancer detection system leverages Convolutional Neural Networks (CNNs) for automated analysis of CT scan images from the LUNA16 dataset. As shown in figure 3.1, the process involves importing, preprocessing, and extracting regions of interest (ROIs) based on annotated coordinates using SimpleITK. Normalizing pixel values to a Hounsfield Unit (HU) range, coupled with contrast adjustment and image resizing, prepares the data for model training. To address class imbalance, the dataset is split into balanced training, validation, and test sets, employing Pandas, NumPy, and OpenCV for data handling. The deep convolutional architecture includes layers like convolutional, batch normalization, max-pooling, and dense layers, trained using appropriate loss functions and optimizers with ImageDataGenerator for augmentation. This system amalgamates deep learning and classical machine learning for accurate lung cancer detection, showcasing adaptability and potential for aiding in precise diagnosis from CT scan images, benefiting medical professionals in early detection endeavors.

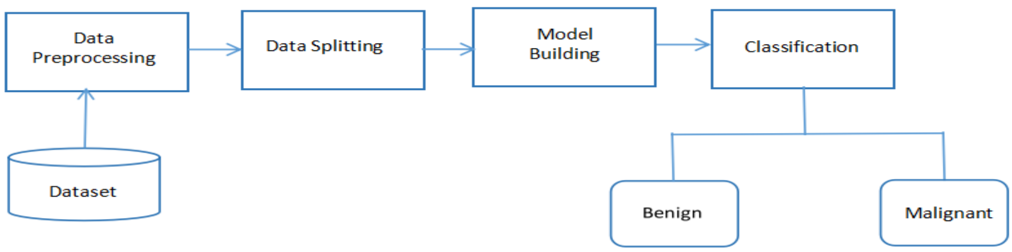


Figure 3.1: Proposed System Design

3.2 Architecture Design

Dataset The dataset used for the project is the LIDC/IDRI database. LIDC/IDRI stands for Lung Image Database Consortium/Image Database Resource Initiative, which is a freely available dataset consisting of CT (Computed Tomography) scans of the chest. It contains 551065 records with 5 attributes as shown in the figure 3.2. The attributes of the dataset are as follows :

- seriesuid
- coordX
- coordY
- coordZ
- class

```
candidates.head(10)
```

	seriesuid	coordX	coordY	coordZ	class
0	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	-56.080000	-67.850000	-311.920000	0
1	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	53.210000	-244.410000	-245.170000	0
2	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	103.660000	-121.800000	-286.620000	0
3	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	-33.660000	-72.750000	-308.410000	0
4	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	-32.250000	-85.360000	-362.510000	0
5	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	-26.650000	-203.070000	-165.070000	0
6	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	-74.990000	-114.790000	-311.920000	0
7	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	-16.140000	-248.610000	-239.550000	0
8	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	135.890000	-141.410000	-252.200000	0
9	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222...	90.102285	-68.430847	-218.243396	0

Figure 3.2: Attributes of the Dataset

3.3 Data Preprocessing

The proposed system involves several critical data preprocessing steps essential for preparing the medical images before model training as shown in the figure 3.3. These steps are crucial in ensuring that the input data is standardized, informative, and suitable for feeding into the machine learning model as shown in the figure 3.4. Here are the key data preprocessing steps:

- **Image Loading and Format Conversion :** The system begins by loading CT scan images using the SimpleITK library, which allows reading medical images which are in specialized formats like MHD. The system uses SimpleITK functions to convert these images into arrays that are compatible with further processing.

- **Region of Interest (ROI) Extraction :** Based on annotations or predefined coordinates, the system extracts ROIs from the CT scan images. They typically contain the areas that are potentially indicative of lung cancer, allowing the model to focus on relevant sections and disregard irrelevant information [12].

- **Image Normalization :** The pixel values in medical images often represent Hounsfield Units (HU). These values are standardized by applying normalization techniques, such as mapping the HU values to a specific range (e.g., from -1000 to 400). Normalization ensures that the images have consistent intensity ranges, which can facilitate model convergence during training.

```
from PIL import ImageEnhance

class PreProcessing(object):
    def __init__(self, image = None):
        self.image = image

    def subtract_mean(self):        #adjusting image brightness by shifting mean
        self.image = (self.image/255.0 - 0.25)*255
        return self.image

    def downsample_data(self):       # reduces the image's size
        self.image = cv2.resize(self.image, (40,40), interpolation = cv2.INTER_AREA)
        return self.image

    def upsample_data(self):         # increases the image's size
        self.image = cv2.resize(self.image, (224, 224), interpolation = cv2.INTER_CUBIC)
        return self.image
```

Figure 3.3: Preprocessing Function

- **Image Enhancement :** The system performs image enhancement techniques to improve the quality and interpretability of the images. Techniques like contrast adjustment are applied to enhance specific features and structures within the images, making them more suitable for analysis.

- **Image Resizing and Augmentation :** To standardize the dimensions and reduce computational complexity, the images are resized to a uniform shape. Additionally, data augmentation techniques, like rotation, flipping, or zooming, are applied to increase the diversity of the training data and improve the model's robustness.

- **Class Balancing :** The system ensures a balanced representation of both positive and negative cases in the training data. Strategies like oversampling, where the minority class is replicated, or under sampling, where the majority class is reduced, are employed to balance the dataset [13].

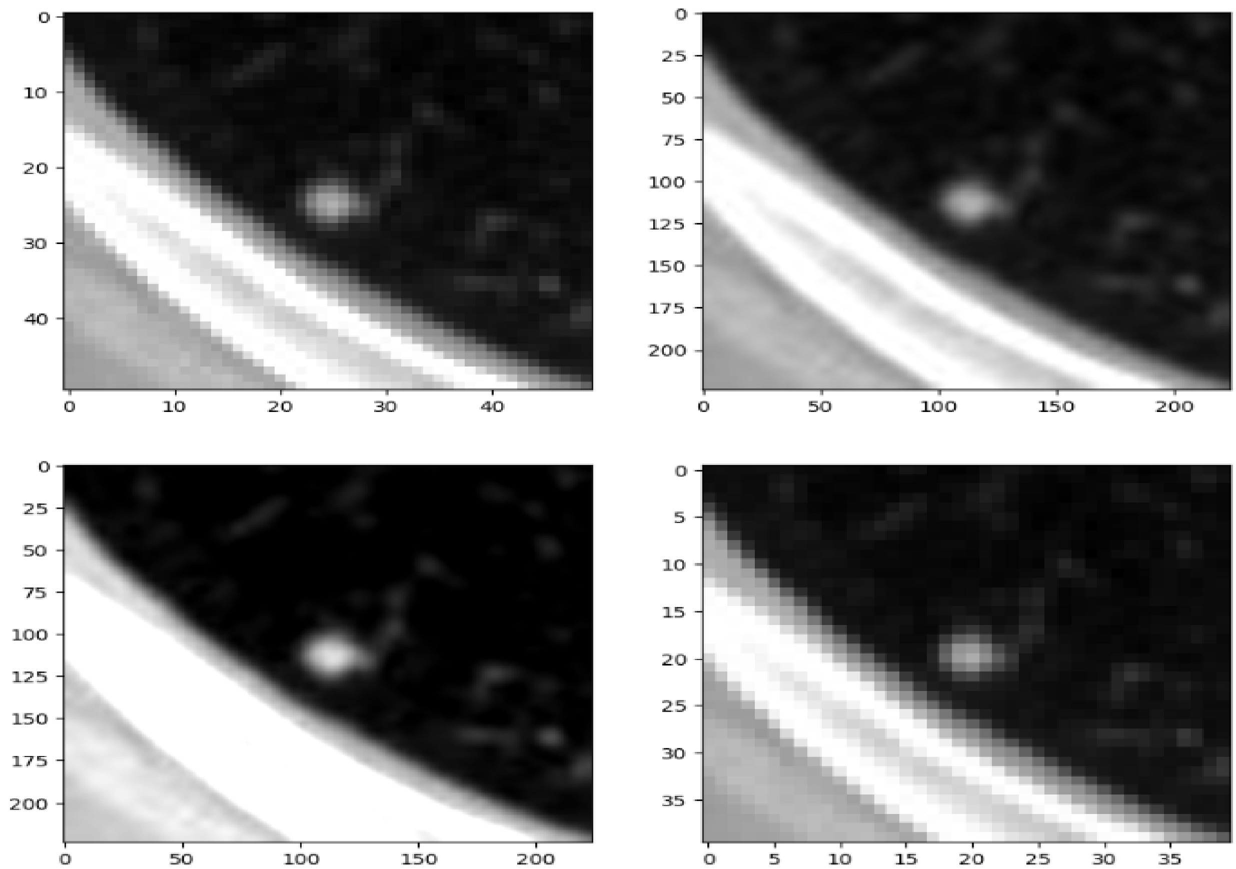


Figure 3.4: Data Augmentation of the images

Chapter 4

Implementation

4.1 Tools and Libraries used

The following are the tools and libraries used involved in the project :

- **Google Colab :** While not a specific Python module, Google Colab is a cloud-based environment utilized here to run Python code interactively, providing access to GPUs and facilitating collaborative coding.
- **Pandas :** Pandas is employed for data manipulation and handling, especially for reading and managing structured data from CSV files.
- **NumPy :** NumPy is essential for numerical computations, especially when dealing with arrays and mathematical operations on large datasets.
- **Matplotlib and Seaborn :** These libraries are used for data visualization, helping in the visualization of images, graphs, and statistical plots.
- **SimpleITK :** SimpleITK is utilized for handling and processing medical images in the DICOM format, enabling functions for image reading, transformation, and extraction of information from medical images.
- **OpenCV :** OpenCV (Open Source Computer Vision Library) is used for various image processing tasks, including reading, processing, and augmenting images. It offers functionalities for computer vision and image analysis.
- **PIL (Python Imaging Library) / Pillow :** PIL or Pillow is used for image processing tasks such as image opening, enhancement, and conversion between different image formats.

- **Scikit-learn :** Scikit-learn is employed for machine learning tasks, including splitting datasets, training traditional classifiers like SVM, XGBoost, and Random Forest, and evaluating model performances.
- **TensorFlow and Keras :** These are fundamental libraries used for building and training neural networks. They provide the backbone for creating and compiling deep learning models.

4.2 Proposed Algorithm

4.2.1 2D-CNN - Convolutional Neural Network

The proposed lung cancer detection algorithm involves using a convolutional neural network (CNN) trained on a dataset of CT scan images. The dataset comprises positive and negative instances of lung cancer, with preprocessing steps including image conversion to NumPy arrays, normalization, resizing, contrast enhancement, and feature extraction using BRISK. The dataset is split into training, validation, and testing sets. A CNN architecture with convolutional layers, batch normalization, max-pooling, dropout, and fully connected layers is employed as shown in the figure 4.1. Data augmentation is utilized to improve model generalization. The model undergoes training, validation, and testing phases, with subsequent evaluation using performance metrics like confusion matrix, classification report, and accuracy to assess its efficacy in detecting lung cancer from CT scan images. We have used different activation functions and observed the performance of the model.

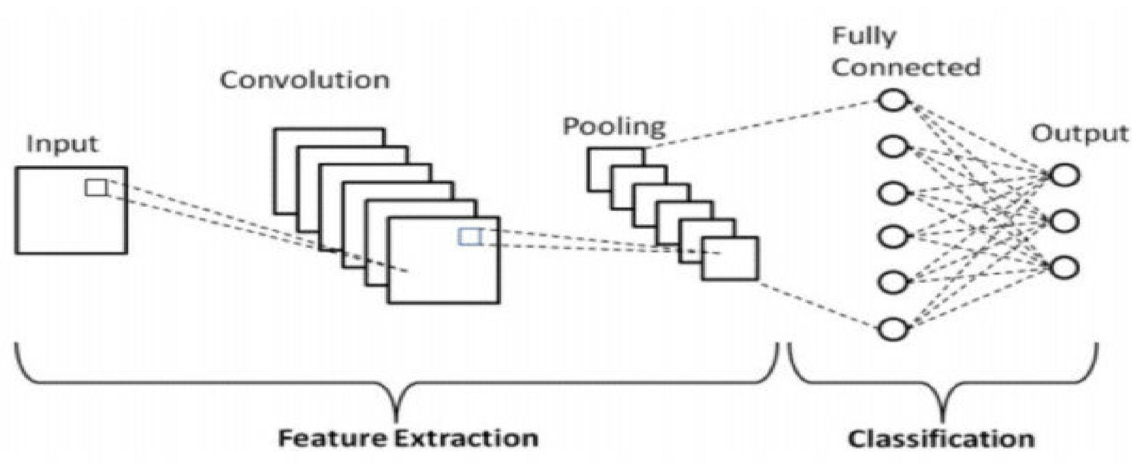


Figure 4.1: 2D-CNN Architecture
(Courtesy:www.researchgate.net/figure/A-simple-CNN-Architecture$_{fig}2_3$63266882)

4.2.2 Activation Functions

Sigmoid : The algorithm employs a Convolutional Neural Network (CNN) architecture for lung cancer detection in CT scan images. During the model configuration, the sigmoid activation function is utilized within the neural network layers. Following data preprocessing and partitioning into training, validation, and testing sets, the CNN is trained using the sigmoid activation function, reaching an accuracy of 93%. Sigmoid, known for its S-shaped curve, is particularly useful in binary classification tasks due to its range from 0 to 1, mapping predictions to probabilities. The model converges well during training, leveraging the sigmoid function to introduce non-linearity and facilitate gradient-based optimization. The accuracy of 93% indicates a strong performance in distinguishing between cancerous and healthy lung tissue areas in the CT scan images.

Softplus : Within the CNN architecture, the algorithm adopts the softplus activation function to detect lung cancer in CT scan images. Softplus, resembling a smoothed version of ReLU, transforms the input values into positive real numbers. The model trained using softplus achieves an accuracy of 94%. Softplus, known for its smoothness and non-linearity, proves beneficial in capturing subtle patterns within the medical images, contributing to its effectiveness in distinguishing between cancerous and healthy lung tissues. The activation function's smoothness ensures gradient stability during backpropagation, facilitating efficient learning and convergence. The 94% accuracy showcases the adaptability of softplus in enhancing the model's sensitivity to detect potential lung cancer areas with commendable performance.

Re-Lu : In this scenario, the algorithm utilizes the Rectified Linear Unit (ReLU) activation function within the CNN architecture for lung cancer detection as shown in figure 4.2. ReLU, known for its simplicity and efficiency, replaces negative values with zero while preserving positive values. Leveraging ReLU as the activation function results in an impressive accuracy of 95%. This achievement signifies the effectiveness of ReLU in mitigating the vanishing gradient problem and accelerating convergence during training. The non-linearity introduced by ReLU aids in learning complex patterns in the CT scan images, distinguishing between cancerous and non-cancerous regions with high accuracy. The robustness of ReLU in enabling faster convergence and reducing computational load contributes significantly to achieving the 95% accuracy in lung cancer detection.

```python
def define_model():
  model = Sequential()
  model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same', input_shape=(50, 50, 1)))
  model.add(BatchNormalization())
  model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(MaxPooling2D((2, 2)))
  model.add(Dropout(0.1))
  model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(MaxPooling2D((2, 2)))
  model.add(Dropout(0.2))
  model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(MaxPooling2D((2, 2)))
  model.add(Dropout(0.3))
  model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(MaxPooling2D((2, 2)))
  model.add(Dropout(0.4))
  model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
  model.add(BatchNormalization())
  model.add(MaxPooling2D((2, 2)))
  model.add(Dropout(0.5))
  model.add(Flatten())
  model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
  model.add(BatchNormalization())
  model.add(Dropout(0.5))
  model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'));
  return model
```

Figure 4.2: Model Definition

4.3 Performance Measure

- The below figures 4.3, 4.4 and 4.5, showcases performance metrics—accuracy, precision, recall, and F1-score—acquired from the 2D - Convolutional Neural Network (CNN) utilized for lung nodule detection.

- It enables a comparative analysis of how these activation functions impact crucial evaluation criteria, including accuracy in detecting lung nodules, precision for positive and negative nodule identifications, recall rates, and F1-scores.

- The accuracy rates achieved by the CNN using Softplus, Sigmoid, and ReLU activation functions are 87%, 94%, and 95% respectively, which represents the overall correctness of nodule detection by the CNN.

- Precision measures the correctness of positive and negative nodule identifications. For benign nodule identification, Precision scores for Softplus, Sigmoid, and ReLU are 97%, 96%, and 97%, respectively. Whereas for malignant nodule identification, Precision scores are 59%, 86%, and 85% for Softplus, Sigmoid, and ReLU, respectively.

- Recall rates, indicating the network's ability to capture actual benign instances, show values of 87%, 97%, and 97% for Softplus, Sigmoid, and ReLU concerning positive nodule identification, respectively. For malignant nodule identification, Recall scores are 89%, 78%, and 86% for Sigmoid, Softplus, and ReLU, respectively.

- F1-Score, which harmonizes Precision and Recall, showcases a balanced measure of the model's performance. The F1-Score percentages for benign nodule identification with Softplus, Sigmoid, and ReLU are 92%, 96%, and 97%, respectively. For malignant nodule identification, F1-Score values are 71%, 82%, and 86% for Softplus, Sigmoid, and ReLU, respectively.

- These metrics collectively offer valuable insights into the CNN's effectiveness in the specialized task of lung nodule detection, providing a comparative analysis of the impact of different activation functions on the network's performance.

Classification report of CNN model with Softplus Activation Function

	precision	recall	f1-score	support
0	0.97	0.87	0.92	1340
1	0.59	0.89	0.71	282
accuracy			0.87	1622
macro avg	0.78	0.88	0.81	1622
weighted avg	0.91	0.87	0.88	1622

Figure 4.3: Classification Report of Softplus Activation Function

Classification report of CNN model with Sigmoid Activation Function

	precision	recall	f1-score	support
0	0.96	0.97	0.96	1340
1	0.86	0.78	0.82	282
accuracy			0.94	1622
macro avg	0.91	0.88	0.89	1622
weighted avg	0.94	0.94	0.94	1622

Figure 4.4: Classification Report of Sigmoid Activation Function

Classification report with ReLu Activation Function

	precision	recall	f1-score	support
0	0.97	0.97	0.97	1340
1	0.85	0.86	0.86	282
accuracy			0.95	1622
macro avg	0.91	0.92	0.91	1622
weighted avg	0.95	0.95	0.95	1622

Figure 4.5: Classification Report of ReLu Function

Chapter 5

Results and Discussions

5.1 Experimental Results

The model that we have proposed has achieved an accuracy of 95%, indicating the overall correctness in classifying lung cancer cases. Moreover, the model exhibited a precision of 97%, signifying its capability to accurately identify positive cases among the predicted instances. The recall, measuring the proportion of actual positive cases correctly identified by the model, stood at 96%. The F1-score, a combined metric considering both precision and recall, yielded a value of 97%. The classification report further detailed the model's performance across multiple metrics for both positive and negative cases. As shown in figure 5.1, the confusion matrix provided a clear visualization of correct and incorrect predictions, offering insights into the model's ability to distinguish between positive and negative instances of lung cancer. Overall, these evaluation metrics collectively indicate the model's robustness in identifying lung cancer cases from CT scan images, highlighting its potential as a tool for automated detection in clinical settings.

```
CONFUSION MATRIX
[[1286   54]
 [  37  245]]
```

Figure 5.1: Confusion Matrix of proposed model

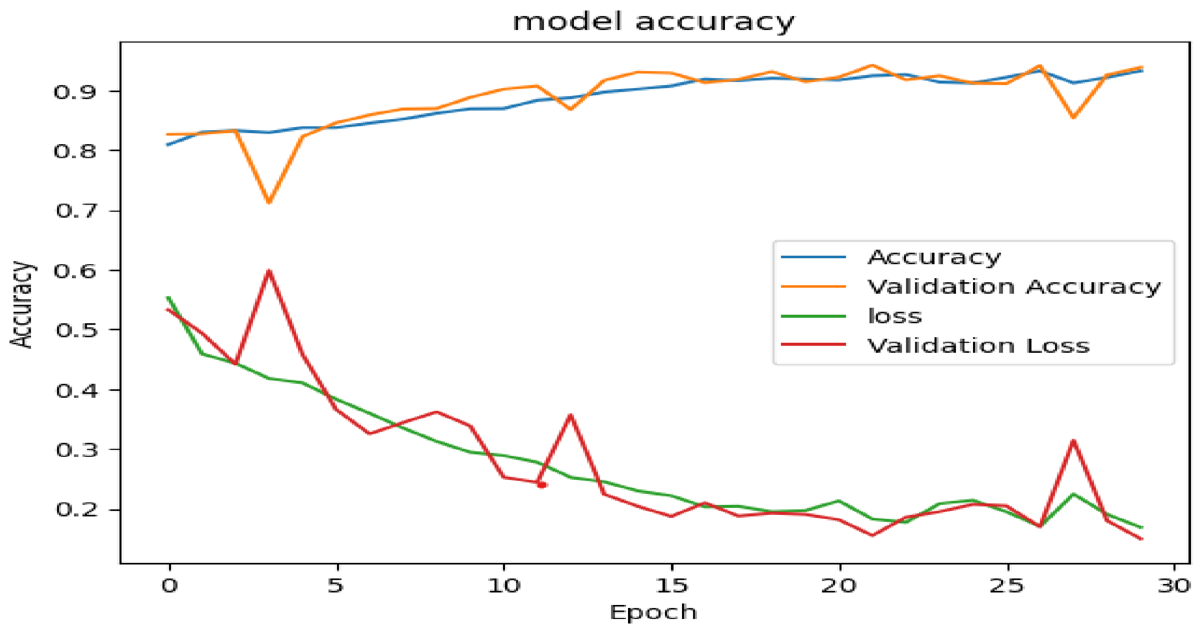


Figure 5.2: Model Performance with Softplus Activation Function

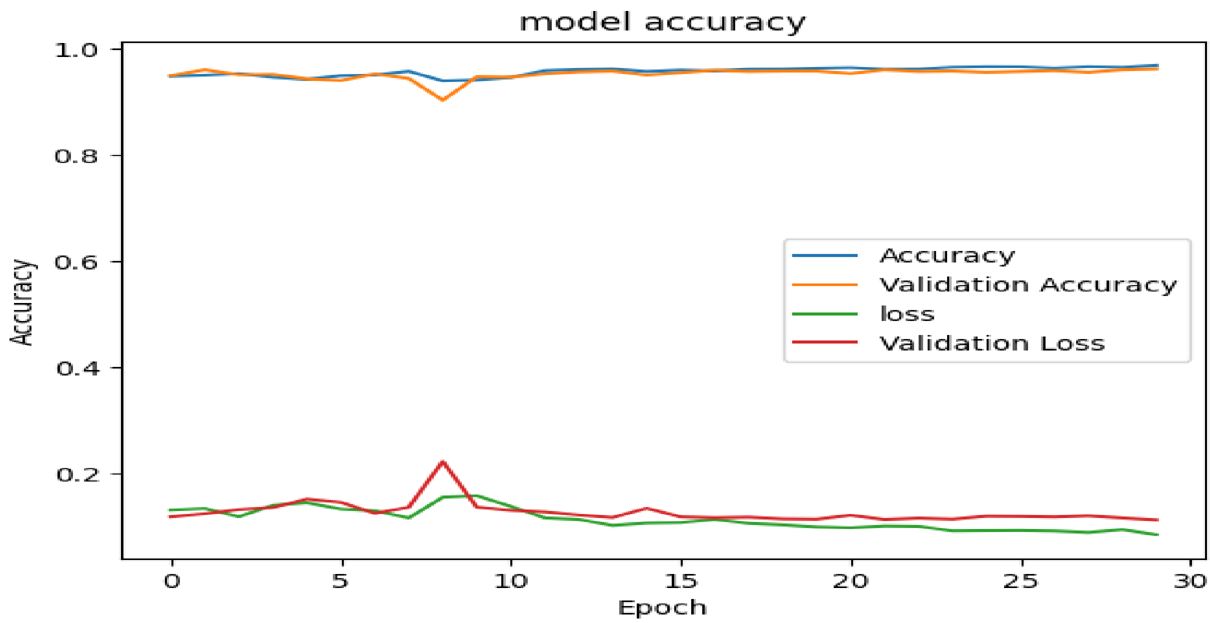


Figure 5.3: Model Performance with Sigmoid Activation Function

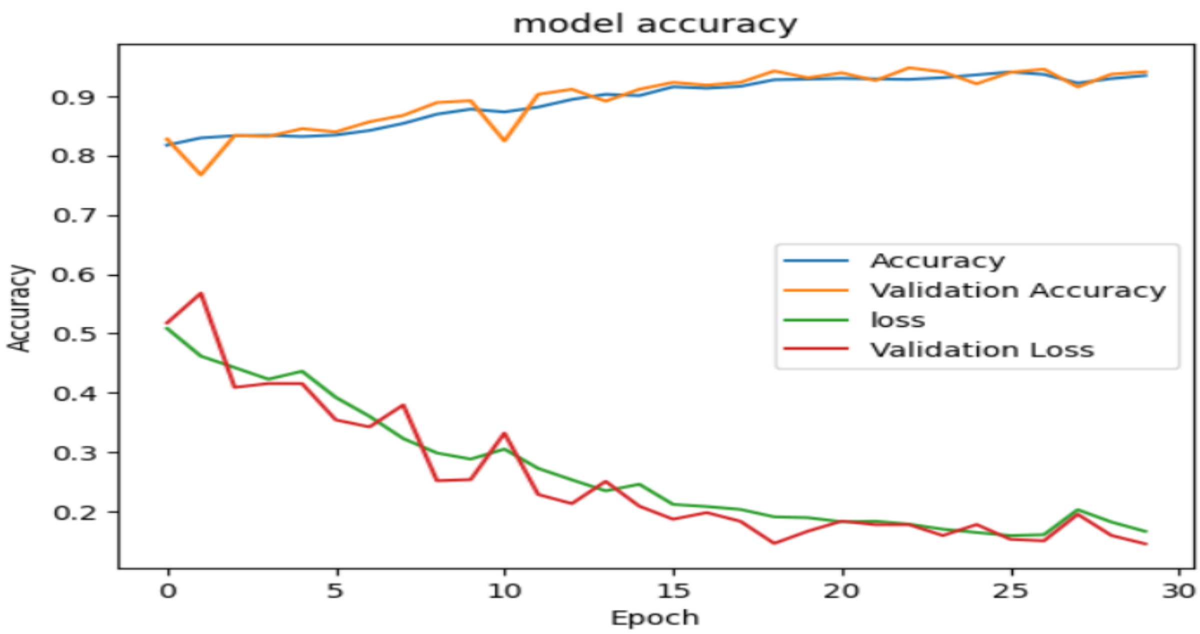


Figure 5.4: Model Performance with ReLu Activation Function

```
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import numpy as np
from PIL import Image

model_new_1 = load_model("classification_deep_conv_model.h5")
image_path = "image_522956.jpg"
img = Image.open(image_path)
img = img.resize((50, 50))
img = image.img_to_array(img)
img = np.expand_dims(img, axis=0)
predictions = model_new_1.predict(img)
threshold = 0.5
predicted_class = 1 if predictions[0][0] > threshold else 0
print("Predicted Class:", predicted_class)
```

```
1/1 [==============================] - 0s 301ms/step
Predicted Class: 1
```

Figure 5.5: Predicting Image Classification Using Pre-trained Convolutional Neural Network (CNN) Model with Keras

Chapter 6

Conclusions and future works

6.1 Conclusion

The project involved the analysis of lung cancer using CT scans and machine learning techniques. The dataset comprised annotations and candidates' information, focusing on positive and negative instances related to lung nodules. The CTScan class facilitated data extraction and manipulation, such as reading metadata, voxel operations, and image normalization. Pre-processing steps like contrast enhancement, downsampling, and upsampling were applied to images. The dataset was split for training, validation, and testing, and data augmentation was performed to balance the classes. Convolutional Neural Networks (CNNs) were implemented using Keras to classify the CT scan images into positive and negative classes. The model architecture consisted of multiple convolutional layers, followed by dense layers. The trained model achieved satisfactory performance on the test set, as evaluated by accuracy metrics. Further assessment using a confusion matrix highlighted the model's ability to classify lung nodule instances effectively. The project demonstrated a comprehensive workflow, combining data processing, deep learning, and model evaluation to analyze and classify lung nodules in CT scans, contributing to potential diagnostic applications in lung cancer detection.

6.2 Future Works

Interactive Visual Analytics : Creating an interactive visualization dashboard that presents patient demographics, environmental factors, and tumor characteristics through scatter plots, histograms, and heatmaps, empowering clinicians to explore correlations effortlessly. Additionally, integrating geographical maps to illustrate cancer prevalence across regions provides insightful perspectives on po-

tential environmental risk factors.
Temporal Analysis and Predictive Modeling : Integrating time-series analysis and predictive modeling enhances the understanding of disease progression and enables the identification of potential cancer development indicators using visual representations like line charts or stacked area plots. These approaches leverage sequences of medical images to forecast tumor characteristics over time, assisting clinicians in tailoring more personalized interventions and anticipating responses to treatments.
3D Visualization and Patient Education : Creating immersive 3D anatomical models and virtual reality (VR) visualizations using medical imaging data aims to enhance patient education and aid surgical planning. These interactive visualizations enable exploration of tumors and affected regions, empowering patients and healthcare professionals to make informed decisions and better understand treatment procedures and potential outcomes.

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