Lung Risk and Severity Prediction

Introduction

Lung diseases, including lung cancer and other respiratory conditions, are among the leading causes of mortality worldwide. Early detection and severity prediction are crucial for timely treatment and improved patient outcomes. In this research, we aim to analyze available datasets and machine learning models to determine the best approach for predicting lung disease severity and risk.

Dataset Selection

We explored multiple publicly available datasets to identify the most suitable one for our study. Among the datasets examined, we found that the dataset quality and annotation accuracy significantly impacted the model's performance. The primary datasets considered are:

1. LungNet22

- Source: Available on the internet
- Contains: Annotated chest CT images
- Limitation: Inconsistencies in annotations and varying image quality affected model performance.

2. Roboflow Datasets

- **Chest CT Dataset** (used in this project)
- **Lung Cancer Dataset**
- Strengths: Easily accessible and diverse data samples.
- Weaknesses: Annotations are not optimal, leading to lower mAP (mean Average Precision) values.

Despite analyzing several datasets, we observed that the model's mAP value was consistently low due to dataset quality and annotation inaccuracies.

Best Model for Lung Disease Prediction

After extensive research, we found that **The Sybil AI Model** is currently one of the most effective models used in hospitals for lung disease prediction. This model was developed using high-quality datasets from reputable sources and has demonstrated superior performance in risk assessment and severity prediction.

Training and Evaluation Data for Sybil Model

- **Training Data:**
    - 6,839 LDCT (Low-Dose Computed Tomography) scans from the **National Lung Screening Trial (NLST)** dataset.
- **Validation Data:**
    - 6,282 additional LDCT scans from the NLST dataset.
- **External Testing:**
    - **Massachusetts General Hospital (MGH):** 8,821 LDCT scans.
    - **Chang Gung Memorial Hospital (CGMH) in Taiwan:** 12,280 LDCT scans, including participants with varying smoking histories, including non-smokers.

Despite our best efforts, we could not obtain access to the **NLST, MGH, and CGMH datasets** within the short time available. These datasets are crucial for building a highly accurate lung disease prediction model.

Dataset Preparation for Training

To build a robust model, we need to structure the dataset with both categorical labels and corresponding CT scans. The dataset will be annotated with bounding boxes to detect lung health status and estimate lifespan predictions. Our dataset should follow these categories based on **The Sybil Model's** methodology:

Lung Cancer Risk Prediction Categories

The model will predict lung cancer risk probabilities across six time windows:

1. **1 Year**
2. **2 Years**
3. **3 Years**
4. **4 Years**
5. **5 Years**
6. **6 Years**

These predictions will be made by analyzing a single low-dose chest CT scan to assess the likelihood of developing lung cancer within the given timeframe.

CT Scan Image Resolutions and Size Standardization

To ensure consistency and improve model accuracy, we need to define the following:

- **Resolution Standardization:** Optimal CT scan resolution for training should be standardized to ensure uniformity across datasets.

- **Image Size Organization:** Images should be resized to maintain clarity and ensure compatibility with deep learning models.
- **Date-Time Metadata:** Every CT scan should be labeled with its corresponding date and time to track disease progression over time.
- **Hospital Data Collection:** Collaboration with hospitals to obtain high-quality, well-annotated scans for model training.

Tech Stack

1. **Programming Language**: Python
2. **Framework**: Streamlit (for UI)
3. **Deep Learning**: PyTorch, Ultralytics YOLO (for object detection)
4. **Computer Vision**: OpenCV, PIL (for image processing)
5. **Data Handling**: NumPy (for array manipulations)
6. **Deployment**: Local system execution with model inference

Solution Code Summary

1. **Model Loading**: The system loads a YOLO model trained on lung disease detection from a local directory.
2. **Prediction Pipeline**:
    - Accepts an input chest X-ray or CT scan.
    - Detects regions affected by lung diseases like cancer or nodules.
    - Calculates the affected lung area and classifies severity into **Mild, Moderate, or Severe**.
3. **Visualization**:
    - Draws bounding boxes around detected abnormalities.
    - Displays the processed image along with a severity assessment.
4. **UI & Customization**:
    - Built using Streamlit with an intuitive image upload option.
    - Includes animated GIF backgrounds and a styled UI for an enhanced user experience.

Here's a breakdown of how the **YOLO model prediction methodology** works and how the **severity classification** is determined.

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1. YOLO Model Prediction Workflow

The **YOLO (You Only Look Once)** model is used for detecting lung diseases from chest CT scans or X-rays. Here's the step-by-step process:

- **Step 1: Load the Pretrained Model**
  - The YOLO model (e.g., best.pt) is loaded using the Ultralytics YOLO library (yolov5 or yolov8).
  - The model has been trained on labeled lung disease datasets where bounding boxes and classes (e.g., "cancerous", "nodule", "normal") are predefined.

```
from ultralytics import YOLO


# Load the trained model
model = YOLO("best.pt") # Load the custom-trained lung disease model
```

- **Step 2: Make Predictions on an Input Image**
  - The model takes an input chest CT scan or X-ray and processes it through the YOLO architecture.
  - The model outputs:
    1. **Bounding boxes** around detected abnormalities.
    2. **Class labels** (e.g., lung cancer, nodules, etc.).
    3. **Confidence scores** (probability of detection accuracy).

```
import cv2


# Load an input image
image_path = "test_image.jpg"
image = cv2.imread(image_path)


# Perform prediction
results = model(image)


# Extract detections
for result in results:
    boxes = result.boxes  # Bounding boxes
    labels = result.names  # Class labels
    scores = result.probs  # Confidence scores
```

2. Severity Classification Methodology

The severity of lung disease is determined based on the following factors:

🔹 **Step 1: Extract Affected Lung Area**

- The **bounding box dimensions** from YOLO help calculate the **total affected area** in pixels.
- We compare the affected area against the total lung area in the scan.

```
# Calculate affected area from YOLO bounding boxes
affected_area = 0
total_area = image.shape[0] * image.shape[1]  # Total pixels in the scan

for box in boxes:
    x1, y1, x2, y2 = box.xyxy[0]  # Get bounding box coordinates
    box_area = (x2 - x1) * (y2 - y1)  # Compute bounding box area
    affected_area += box_area  # Sum up affected areas

# Compute affected percentage
affected_percentage = (affected_area / total_area) * 100
```

🔹 **Step 2: Define Severity Levels**

Based on the **affected percentage**, we classify the severity as:

Affected Area %	Severity Level
0 - 10%	**Mild**
10 - 30%	**Moderate**
>30%	**Severe**

```
# Severity classification logic
if affected_percentage < 10:
    severity = "Mild"
elif affected_percentage < 30:
    severity = "Moderate"
else:
    severity = "Severe"
```

```
print(f"Lung disease severity: {severity}")
```

---

3. Displaying Results

- The final results, including **bounding boxes, labels, and severity level**, are displayed on the image using OpenCV.

```
import matplotlib.pyplot as plt


# Draw bounding boxes on the image
for box in boxes:
    x1, y1, x2, y2 = map(int, box.xyxy[0])
    cv2.rectangle(image, (x1, y1), (x2, y2), (0, 255, 0), 2)  # Green box for detection
    cv2.putText(image, severity, (x1, y1 - 10), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 255, 0), 2)


# Display the image
plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
plt.axis("off")
plt.show()
```

---

4. Key Takeaways

1. **YOLO detects lung abnormalities** by drawing bounding boxes on CT scans.
2. **Affected lung area is computed** from bounding box sizes.
3. **Severity is determined** based on the percentage of affected lung tissue.
4. **Results are visualized** with bounding boxes and severity classification.

From the training log in the image, here’s a breakdown of the model's performance and key metrics:

🔹 **Model Overview**

- **Dataset Size:**
    - **Total images:** 10,780
    - **Training set:** 9,419 images
    - **Validation set:** 907 images

    - **Test set:** 454 images
- **Classes:**
    - 0: Cancer Malignant
    - 1: Nodule
    - 2: Multiple Nodules
- **Training Duration:** ~5.15 hours for 50 epochs
- **Hardware Used:** NVIDIA RTX 3050 (6GB VRAM) with CUDA

🔹 **Model Performance Metrics**

The model was evaluated using the following metrics:

1️⃣ Loss Metrics

These values indicate how well the model is learning:

- **Box Loss**: Measures how well the predicted bounding box aligns with the ground truth.
- **Classification Loss**: Measures how well the model classifies detected objects.
- **DFL (Distribution Focal Loss)**: Measures the quality of object localization.

📌 **Final Values (Epoch 50/50):**

- **Box Loss**: 0.4289
- **Cls Loss (Classification Loss)**: 0.8016
- **DFL Loss**: 0.975

Lower loss values indicate better performance.

2️⃣ Precision, Recall, and mAP

These are key detection performance metrics:

Metric	Value
Precision (P)	0.975
Recall (R)	0.975
mAP@50	0.986
mAP@50-95	0.922

📌 **Interpretation:**

- **Precision (0.975):** When the model predicts a disease, it is correct 97.5% of the time.

- **Recall (0.975):** The model correctly detects 97.5% of all actual disease cases.
- **mAP@50 (0.986):** The model achieves 98.6% accuracy at an IoU threshold of 50%.
- **mAP@50-95 (0.922):** The model maintains 92.2% accuracy over multiple IoU thresholds (more strict evaluation).

Class-wise Metrics

The breakdown of precision, recall, and mAP per class:

Class	Precision	Recall	mAP@50	mAP@50-95
0 (Cancer Malignant)	0.975	0.975	0.986	0.923
1 (Nodule)	0.994	0.994	0.974	0.915
2 (Multiple Nodules)	0.994	0.994	0.975	0.903

📌 **Interpretation:**

- Class 1 (Nodule) has slightly better performance than 0 and 2, with very high recall.
- The model performs well across all classes, with minor variations.

🔹 **Final Thoughts**

✅ **Strengths:**

- High **precision (97.5%)** and **recall (97.5%)** indicate strong performance.
- **High mAP (98.6%)** ensures accurate detection.
- Well-optimized training on **NVIDIA RTX 3050 (6GB)**.

⚠️ **Possible Improvements:**

- Fine-tuning hyperparameters to reduce classification loss.
- Adding more diverse samples for better generalization.
- Testing on real-world images to verify model robustness.

YOLO Model Inference Code with Streamlit UI and Results

```
import streamlit as st
import cv2
import numpy as np
from PIL import Image
import torch
from ultralytics import YOLO
import base64

def load_model():
    model = YOLO(r"C:\Users\iproat26\Desktop\project\Lung Diesease Prediction\runs\detect\train8\weights\best.pt")  # Replace with actual model path
    return model

def predict(image, model):
    results = model(image)
    bounding_boxes = []
    total_area = image.shape[0] * image.shape[1]
    affected_area = 0
    class_labels = {0: "Cancer", 1: "Nodule", 2: "Multi Nodule"}
    detected_classes = []

    for result in results:
        for box in result.boxes:
            x1, y1, x2, y2 = box.xyxy[0].cpu().numpy()
```

```
            confidence = box.conf[0].cpu().numpy()
            class_id = int(box.cls[0].cpu().numpy())
            box_area = (x2 - x1) * (y2 - y1)
            affected_area += box_area
            bounding_boxes.append([int(x1), int(y1), int(x2), int(y2), class_id])
            detected_classes.append(class_labels[class_id])

    severity_percentage = (affected_area / total_area) * 100
    severity_label = categorize_severity(severity_percentage)

    return bounding_boxes, severity_percentage, severity_label,
detected_classes

def categorize_severity(severity_percentage):
    if severity_percentage < 10:
        return "Mild"
    elif severity_percentage < 30:
        return "Moderate"
    else:
        return "Severe"

def draw_bounding_boxes(image, bounding_boxes):
    colors = {0: (255, 0, 0), 1: (0, 255, 0), 2: (0, 0, 255)}
    for box in bounding_boxes:
        x1, y1, x2, y2, class_id = box
        color = colors[class_id]
        cv2.rectangle(image, (x1, y1), (x2, y2), color, 2)
```

```
    return image

# Streamlit UI Customization
st.set_page_config(page_title="Lung Cancer Prediction", layout="wide")


def get_base64_of_gif(file_path):
    with open(file_path, "rb") as file:
        encoded_gif = base64.b64encode(file.read()).decode()
    return encoded_gif

bg_gif = get_base64_of_gif("bg.gif")

# background-image: url("{bg_gif}");

# Background styling with your GIF
page_bg_img = f'''
<style>

.block-container {{
          padding-top: 0rem;  /* Or any value you want */
          padding-bottom: 0rem; /* Optional: adjust bottom padding */
       }}

[data-testid="stAppViewContainer"] {{
    background-image:
url("https://media3.giphy.com/media/v1.Y2lkPTc5MGI3NjExcTl2MjFzdG1iYjR
```

```
qdjcxazdoOWEyNjdjbWM2YWhkYTFrMnZnamVvdiZlcD12MV9pbnRlcm5hbF9
naWZfYnlfaWQmY3Q9Zw/dt0KXLj7bzwZuRQBwY/giphy.gif");
   background-size: 45% auto;
   background-repeat: no-repeat;
   background-position: right center;
   background-attachment: fixed;
   padding-top: 0px;
}}

[data-testid="stHeader"] {{
   background: rgba(0, 0, 0, 0);
}}

/* File uploader styling */
[data-testid="stFileUploader"] {{
      width: 50%; /* Or any desired width */
      float: left; /* Or any desired layout */
   }}

.st-emotion-cache-1gulkj5 {{
   width: 100% !important;
   max-width: 100% !important;
}}

.st-emotion-cache-7ym5gk {{
   width: 100% !important;
   max-width: 100% !important;
```

```
}}

/* Content container */
.st-emotion-cache-1v0mbdj {{
    margin: 0 auto;
    display: block;
}}

/* Column styling */
.st-emotion-cache-1kyxreq {{
    justify-content: center;
}}
</style>
'''

st.markdown(page_bg_img, unsafe_allow_html=True)

st.title("🫁 Lung Cancer Detection & Severity Assessment")
st.subheader("Upload a Chest X-ray or CT Scan 🔬 ")
model = load_model()

uploaded_file = st.file_uploader("Choose an Image", type=["jpg", "png",
"jpeg"])
if uploaded_file:
    image = Image.open(uploaded_file)
    image = np.array(image)
```

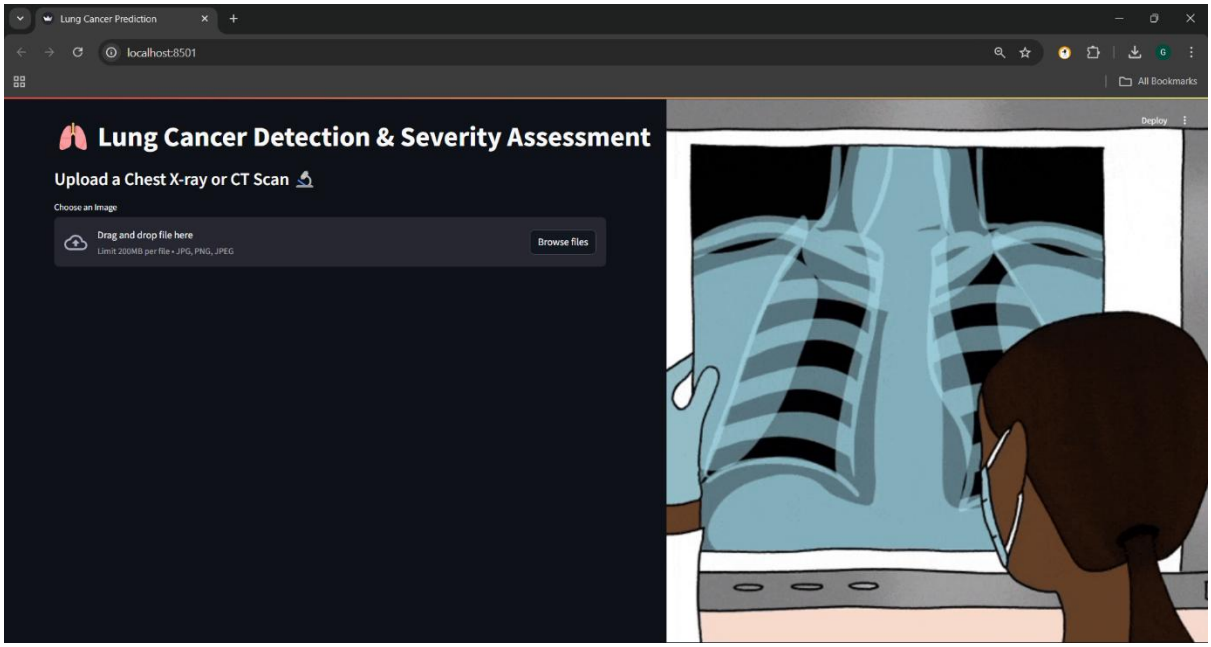
```
    bounding_boxes, severity_percentage, severity_label, detected_classes =
predict(image, model)


    image_with_boxes = draw_bounding_boxes(image.copy(),
bounding_boxes)


    col1, col2 = st.columns([3, 2])
    with col1:
        st.image(image_with_boxes, caption="Detection Results")
    with col2:
        st.markdown(f"### 🩻 Severity Level: {severity_label}")
        st.markdown(f"**Affected Area:** {severity_percentage:.2f}% of Lungs")
        st.markdown(f"### 🔍 Detected Conditions:")
        for cls in set(detected_classes):
            st.markdown(f"- **{cls}**")
```

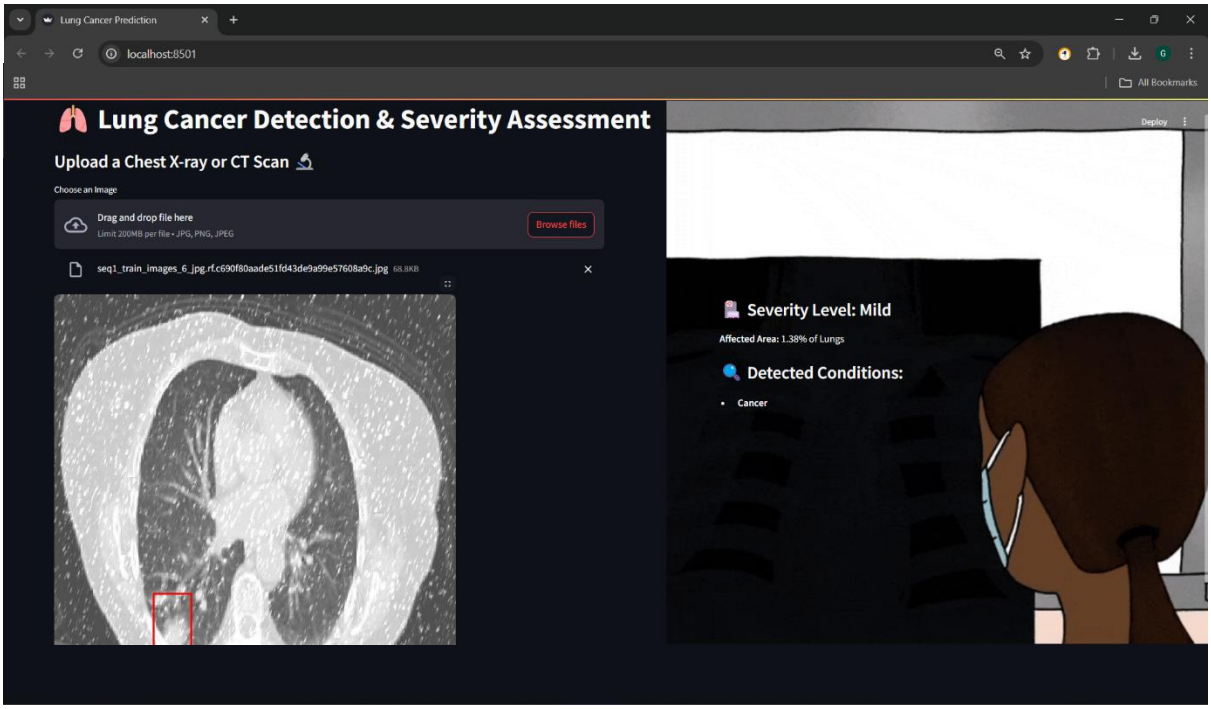
output:

0: 640x640 1 0, 84.4ms

Speed: 14.5ms preprocess, 84.4ms inference, 6.8ms postprocess per image at shape (1, 3, 640, 640)

OUTPUT IN UI:


Lung Cancer Prediction
localhost:8501
All Bookmarks
Lung Cancer Detection & Severity Assessment
Upload a Chest X-ray or CT Scan
Choose an Image
Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG
Browse files
Deploy


Lung Cancer Prediction
localhost:8501
All Bookmarks
Lung Cancer Detection & Severity Assessment
Upload a Chest X-ray or CT Scan
Choose an Image
Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG
Browse files
seq1_train_images_6_jpg.rf.c690f80aade51fd43de9a99e57608a9c.jpg 68.8KB
Deploy
Severity Level: Mild
Affected Area: 1.38% of Lungs
Detected Conditions:
Cancer

Git Repo and code details:

REPO: https://github.com/K-GOKULAPPADURAI/Lung-Cancer-Prediction-With-Severity.git