PREDICTION OF LUNG CANCER FROM LOW-DOSE CT IMAGES

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Özetçe **—Kanserin erken teşhisi, sonuçları ve hasta sağkalım oranlarını önemli ölçüde arttırmaktadır. Derin öğrenme teknikleri, tıbbi görüntü analizinde benzersiz bir yaklaşım sunmaktadır. Geleneksel yöntemlerin aksine, derin öğrenme algoritmaları, Bilgisayarlı Tomografi (BT) görüntüleri gibi ham verilerden otomatik olarak hiyerarşik temsiller öğrenebilir. Bu nedenle, akciğer kanseri taramasında nodül tespiti ve sınıflandırılması için kapsamlı sistemler geliştirmeyi amaçlıyoruz.**

Derin öğrenmenin potansiyeli, görsel analizdeki gözlemci değişkenliğini azaltmakta ve tutarlı ve güvenilir teşhisler sağlamaktadır. Ayrıca, akciğer kanseri taramasında yaygın olarak kullanılan yüksek dozlu BT taramalarıyla ilişkilendirilen risklerin azaltılmasının bir perspektifini sunar. Düşük dozlu BT taramalarından anlamlı bilgiler çıkarılarak radyasyon maruziyetinin en aza indirilmesi ve teşhis etkinliğinin korunması hedeflenmektedir, hasta güvenliği öncelikli tutulmaktadır ve erken teşhis girişimlerine erişimi arttırmaktadır.

Ayrıca, dünya çapında doktorların erişimine olanak sağlayan bir web uygulaması geliştirmeyi hedefleyen araştırma, bu teknolojinin küresel erişimini vurgulamaktadır. Kullanıcı dostu bir platform oluşturarak, farklı bölgelerden doktorlar, akciğer kanseri tespiti için derin öğrenme tabanlı araçları kullanabilir, teşhis kapasitelerini artırabilir ve sınırların ötesinde bakım uygulamalarını standartlaştırabilir. Bu girişim, akciğer kanseriyle mücadele çabalarının işbirlikçi ve kapsayıcı doğasını vurgular, küresel ölçekte hasta sonuçlarını iyileştirme vaat eder.

Anahtar Kelimeler—Derin Öğrenme, Düşük Doz BT, Akciğer Kanseri, Akciğer Nodülü

Abstract—**Early detection of the cancer significantly improves the outcomes and patient survival rates. Deep learning techniques offer a unique approach in medical imaging analysis. Deep learning algorithms can learn hierarchical representations from raw data automatically, such as Computed Tomography (CT) images. Therefore, we aim to develop comprehensive systems for identifying and categorizing nodules in lung cancer screening.**

Deep learning's potential lies in reducing observer variability in visual analysis, providing consistent and reliable diagnoses. Additionally, it offers the prospect of mitigating risks associated with high-dose CT scans commonly used in lung cancer screening. By extracting meaningful information from low-dose CT scans, it is aimed to minimize radiation exposure while maintaining diagnostic efficacy, prioritizing patient safety and increasing accessibility to early detection initiatives.

Moreover, the research aims to develop a web application accessible to doctors worldwide highlighting the global reach of this technology. By creating a user-friendly platform, doctors from different regions can utilize deep learning-based tools for lung cancer detection, enhancing diagnostic capabilities and standardizing care practices across borders. This initiative underscores the collaborative and inclusive nature of efforts to combat lung cancer, promising to improve patient outcomes on a global scale.

Keywords—Deep Learning, Low Dose CT, Lung Cancer, Lung Nodule

I. INTRODUCTION

This Project aims to provide an effective solution to detection of early-stage lung cancer from low-dose CT scans. Comparing to high dose CT scans, low dose CT scans provides less risk and lower radiation exposure. However, it also decreases the scan quality and its readability. Therefore, it is important to use techniques of deep learning to enhance the scan quality and detect the nodules that might turn into cancer.

Specifically engineered 3D CNN is used as a model which is designed for medical image processing. A web-based UI is also developed that gets the ct scans as input and provides an enhanced image and detection result. The ct scans gotten from the UI sends back to the server. The server process the image and provides a detection result. The result is sent back to the UI so the doctors can make sense of it and provides needed medical treatment to the patient.

II. PRELIMINARY EXAMINATION

This project aims to create an web application that is capable of detecting lung nodules from low-dose CT Scans with the help of a model that is specifically trained for this. In the training phase, cnn is going to be used and tested with real life patients. The noble part of this project is the creation of a wab application for low-dose CT scans.

A. Literature Review

In their study, Wenfa Jiang and colleagues proposed a nodule detection network named Nodule-Net and achieved successful results on the test set. They also obtained competitive outcomes compared to other solutions in the LUNA 16 competition. In the task of False Positive Reduction, the 3D U-Net method that uses weighted cross-entropy handled the imbalanced samples while recording a final FROC value of 0.883 on the test set. For the malignant and benign classification of lung nodules, successful results were obtained using the 3D U-Net architecture. [1].

Imran Shafi and his colleagues conducted their study using the LUNA 16 dataset. In the study, a comparison was made between standalone machine learning models and the proposed SVM + CNN hybrid model. The results shows that hybrid models have better performance than standalone models. It is shown that models supported by CNN significantly improve classification accuracy. Hybrid models achieved the highest accuracy scores, with the proposed CNN+SVM model reaching the top accuracy of 94%. [2].

Bryce Dunn and his colleagues have proposed a procedure using the iM-RRN deep learning method. Th method aims to improve the accuracy of automatic segmentation on independent lung CT data. Additionally, they highlight the importance of addressing data imbalance and employing an appropriate balancing method. The study demonstrates that subtypes of lung cancer can be classified in a semi-automatic manner without the need for radiologist intervention.[3].

Hamdalla F. Al-Yasri and his colleagues have also developed a computer-aided diagnosis scheme for early detection of cancer. The suggested model uses data provided from chest CT images.The project aims to improve a CNN deep learning model that can accurately identify and categorize lung cancer nodules. When the model is applied to the dataset, it achieves an accuracy of 93.548%, a sensitivity of 95.714%, and an approximately 95% specificity [4].

In their study, Wafaa Alakwaa and colleagues developed a method for detecting nodules in lung cancer patients using a deep convolutional neural network (CNN) and U-Net architecture. Using the pre-processing methods for 3D CNN shows the best performance on the test set. They achieved a high AUC value of 0.83, while using less labeled data compared to many state-of-the-art CAD systems. It was shown that only a training database is required for training the network. The importance of this study is its potential for generalization to other types of cancer [5].

Lakshmanaprabu and colleagues demonstrated in their study that the proposed feature reduction with ODNN outperforms other classification methods in lung CT images. With the help of this automatic classification method, human mistake is avoided and manual labeling time is decreased .Techniques of Machine learning were used to accurately identify abnormal and normal lung pictures. The results indicate that the technique is effective. Additionally, the strategy was shown to be fast, user-friendly and cost-effective. [6].

In this study, Su Chen developed a convolutional neural network model for the diagnosis of malignant and belign lung nodules. In experiments, it was observed that the developed model lowers the complexity of the algorithm while increasing the detection rate of lung nodules. The 3D U-net model is used in the study. It was created by combining CNN and LSTM RNN. This method enables the model to learn finer features compared to methods that only use CT images. The model can predict malignant nodules with 92.3% accuracy and benign nodules with 82.8% accuracy of. These results demonstrate that the system is effective and applicable [7].

Hu Chen and his colleagues incorporated a deconvolutional network and skip connections into a CNN model. They termed it as a residual decoder-encoder convolutional neural network (RED-CNN). Their approach aims to improve the accuracy of automatic segmentation on lung CT data. Moreover, they showed a noise reduction model that begins with a simple FBP reconstruction from a low-dose scan. It solves the image denoising issue within the image domain. Their study demonstrated a residual autoencoder network which combines an autoencoder (AE) and CNN. It is developed to improve image denoising for LDCT scans. Furthermore, they highlighted the effectiveness of patch extraction techniques for the limited sample size which is typical in clinical imaging. Their research showed the success of RED-CNN over other methods in terms of various metrics. This highlights its potential for enhancing lung cancer detection from low-dose CT scans. Poisson noise was also added to the sinograms that were generated from the normal-dose images to create LDCT images. [8].

Kang and his colleagues proposes a deep learning approach for low-dose computed tomography. This method demonstrate great performance and they got the second place award in the 2016 AAPM Low-Dose CT Grand Challenge. They demonstrate that a feed-forward denoising can be used as the initial iteration of a frame-based denoising algorithm. The goal of their paper is to combine the capacity of deep neural networks with the performance of framelet-based denoising algorithms. Their approach differs from recent learning-based optimization proposals because it offers a network that is no longer a black box. It can be modified for specific restoration tasks. they traine two networks which uses optimization of stochastic gradient descent (SGD) with a minibatch size of 10. The trained networks are a feed-forward network and an RNN. Random Gaussian distribution is used to initialize convolution kernels. They have a learning rate which starts at 0.01 and gradually decreasing to lower values. [9].

Geng and his colleagues present unsupervised deep learning (DL) method for the low-dose CT enhancement challenge. The method incorporates unlabeled low-dose computed tomography sinograms into network training. This method considers the noise distribution and structural characteristics in the sinograms. It also shows success in case of proper gradient learning in a pure unsupervised manner. Some of the most important contributions of this work include the proposal of a unsupervised DL regime, eliminating the need for supervised CT sinogram pairs and facilitating the utilization of unlabeled low-dose sinograms. Moreover, the authors extend this method to a semi-supervised version. They integrate supervised and unsupervised information to construct objective functions. This approach shows better result in terms of computational speed and accuracy on real low-dose CT sinograms when compared to traditional methods [10].

Ciompi and his colleagues propose a unified system that is capable of classifying all relevant nodule types. The model is based PanCan's malignancy probability model and Lung-RADS assessment categories. By the inspirations from their prior experiences, they design a classification framework. In their work they utilized CNN. They specifically used a multi-scale multi-stream architecture. This approach processes multiple triplets of a nodule at various scales simultaneously. It determines the probability of the nodule. They view nodule analysis as a 2D patch combination. It is shown to be a successful method to extract a number of 2D views from a nodule. They trained their deep learning system with data from the Multicentric Italian Lung Detection (MILD) trial. It includes 943 patients and 1,352 nodules. They also validate the system using independent data gathered by the Danish Lung Cancer Screening Trial which consists of 468 patients and 639 nodules. Moreover, they trained a linear support vector machines classifier. The aim of this is to compare the performance of their deep learning architecture with classical approaches. This is used to classify features which is learned from raw data and raw nodule intensity [11].

Polat and his colleagues worked on lung cancer diagnosis by using deep learning methodologies. They showed success in automatic feature extraction. They investigate various Convolutional Neural Network (CNN) architectures for classifying lung CT scan images. The data is used from the Kaggle and Science Bowl datasets. Their study demonstrates two 3D-CNN architectures. The first model, Straight 3D-CNN, uses softmax as its conventional classifier. However the second, Hybrid 3D-CNN, integrates Radial Basis Function which is based on Support Vector Machine as its classifier.[12].

Ansari and her colleagues propose a deep neural network architecture modified for denoising low-dose CT images. They use dilated convolutions with varying dilation rates to capture extensive contextual information. They also utilize residual learning with shortcut connections to preserve crucial image details. Additionally, they integrate a non-trainable edge detection layer to extract edges in multiple directions. It is also used for augmenting the network's ability to retain structural information without significantly increasing computational complexity. To optimize performance, they combine mean-square error (MSE) loss with perceptual loss. This ensures the preservation of texture details in the denoised images [13].

Bazrafkan and his colleagues introduce a reconstruction technique that uses an iterative approach. They aim to solve a critical issue in computed tomography (CT) imaging. The traditional reconstruction methods often fail to ensure fidelity between the reconstructed sinogram and the original signal. To solve this, they combine the strengths of the Simultaneous Iterative Reconstruction Technique (SIRT) algorithm with deep learning models. The SIRT algorithm provides the measured sinogram fidelity, while the deep neural network reduces image space loss. The DNN output serves as the starting point for the SIRT algorithm. It guides DNN to produce more realistic reconstructions while preserving the sinogram space fidelity. This approach effectively integrates machine learning as a regularization unit within the SIRT framework which shows improved reconstruction quality in CT imaging [14].

III. System Analysis and Feasibility

The project aims to detect lung nodule from low-dose ct scans by using deep learning technique. 3D CNN is used to detect the nodules and a web application is created to help the doctors use it.

A. Feasibility

1) Time Feasibility: A three-month period was determined to be proper for project completion. The Waterfall approach was used to create the time feasibility aspect.

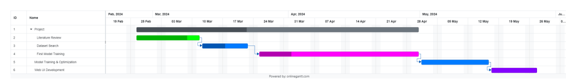

Figure 1 Gantt Schema for Project

2) Technical Feasibility: 1. Data Collection and Preparation:

Data Source:
Bt images will be obtained from publicly available datasets.

Data Quality:
High-resolution and quality datasets are required. Noise, artifacts, and other quality issues may adversely affect the accuracy of the model.

2. Machine Learning Model:
Algorithm Selection:
Deep learning algorithms such as Convolutional Neural Network can be used for image classification.

Model Training:
The dataset should be divided into validation, training and test sets. Measures should be taken against problems like overfitting and underfitting.
Performance Metrics:
Performance metrics such as accuracy, precision, and recall should be determined. These metrics will be used to evaluate the success of the model.
Application and Integration:
Software Development:
Software development is required to make the model work in real-time or offline.

Integration:
APIs or other integration methods necessary for integrating the model with existing health information systems should be determined.

Recommended Steps:
Data Preparation and Preprocessing: Cleaning, normalization, and feature extraction of collected data are necessary.
Model Development and Training: The model should be

developed and trained according to the selected algorithm and architecture.
Performance Evaluation: Comprehensive testing should be conducted to evaluate the performance of the trained model, and the results should be analyzed.

3) Legal Feasibility: All CT images and libraries used in this project have been obtained from open sources, making it free from any legal issues.

4) Economic Feasibility: The cost of the hardware used is 40000 TL, since there are two computers with each one costing 20000.
Bt images will be obtained from publicly available datasets and are free.
The payment for two individuals for 3 months is 16000 * 3 = 48000. So for this project total salary is calculated as 48000 TL. The total budget is 40000 + 48000 = 88000 TL

Table 1 Components and Prices for the Project

Component Name	Price (TL)
Computers (2 units)	20000
Employee Salary (3 months)	48000
Total Budget	**88000**

B. *Elements of the System*

The goal of this project is to create a robot that finds temperature anomalies to prevent overhearing and give a first response to the fire. By doing so, decrease need of hardware, use of human use of human and data resources from heat sensors. The Table 3.2 below provides an overview of the project's two resources which are human and data resources.

Table 2 Resources which are used for the project

Resource	Element
Human Resources	Umut Deşer, Anıl Kutay Uçan
Data Resources	Computer, Google Colab

C. *Use Case Scenarios and Diagrams*

Use case scenarios and diagrams are used to evaluate the possible outcomes and risks of the project.

Use Case Title: Detect Lung Nodule
Primary Actor: User
Supporting Actor: Server
Pre-conditions: The user got the low-dose CT scans in DICOM format

Main Success Scenario:

1) The user uploads the ct scan to the website
2) The website sends the files to the server
3) The server starts the detection algorithm that is trained with deep learning
4) The server gets a result
5) The server sends the result to the website

Extensions:

- 2a. The server receives unsupported format type
  - 2a1. The server sends error

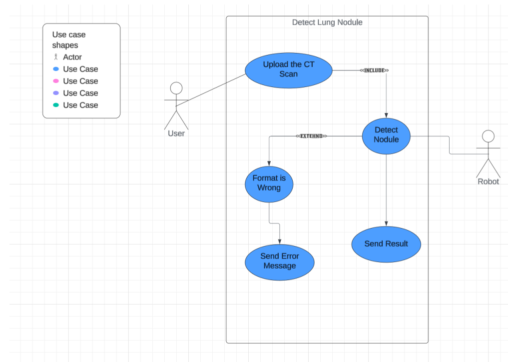

Figure 2 Use Case Diagram For Create Heat Map

IV. System Design

The goal of this project is to train a model with deep learning to detect lung nodules from low-dose CT Scans and create a web UI to make it available through the net.

A. *Dataset Design*

The dataset belongs to Luna16. In the dataset there are over 800 low-dose lung CT scans. The CT scans are in the format of mhd. The nodule locations are detected by the radiologist. For the training and validation, subsets of this dataset is utilized. 2 subset containing approximately 150 ct scan is used for the training and validation. 20% of the dataset is separated to be used as validation.

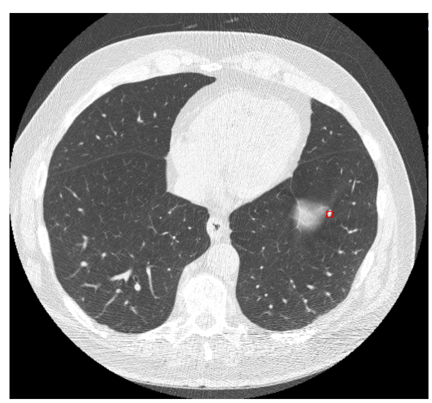

Figure 3 Dataset Example Image

B. Software Design

1) 3D CNN Design: In recent years, medical imaging field has improved thanks to deep learning. Convolutional Neural Networks (CNNs) were important for tasks such as segmentation, classification, and detection. Moreover, 3D Convolutional Neural Networks are important for their ability to capture spatial and temporal information effectively. It makes them well-suited for analyzing volumetric data, such as medical scans. Therefore, to detect lung nodules 3D CNN model is used. The model is proposed by [15] for lung nodule detection. The components of the module is explained in details below.

2) Components of the Model: **Preprocessing Block:** The input data is passed through a preprocessing block, which consists of convolutional layers, batch normalization and activation functions. This block is used to extract low-level features from the input volume.

Feature Extraction Blocks: The core of the model has multiple feature extraction blocks. Each block consists of several PostRes blocks. The PostRes blocks are necessary to learn the deeper and more complex features. By stacking these blocks, the model can extract hierarchical features from the input data.

Pooling and Unpooling Layers: Max-pooling layers are put between the feature extraction blocks to downsample the feature maps and reduce computational complexity. It also retains essential information. Max-unpooling layers are used during the decoding phase to upsample the feature maps to their original resolution.

Skip Connections: To provide the flow of information across different layers of the network, skip connections are used. These connections enable the model to bypass certain layers which allows for the direct transfer of features from the encoder to the decoder. This helps to preserve spatial information and decrease information loss during downsampling.

Input & Output As an input the model receives 128x128x128 3D image in numpy format. Besides this, the bounding box information of the lung is also given to the model. As an output the model gives 32x32x32x3x5 numpy array. The 32 is the downsampled version of the 128x128x128 image. The 3 rows are for the nodule size and 5 rows are for the nodule information. The information contains the z,y,x coordinates of the nodule, the classification of the nodule and the diameter of the nodule. The output can be converted to the nodule position and if there is a nodule or not.

3) Loss Function: Appropriate loss function design is crucial for the success of the model. It guides the training process by decreasing the difference between the ground truth and predicted object properties. The used loss functions are shown below with the explanations.

Classification Loss: The classification loss is responsible for predicting the existence or absence of objects within the input image. For the model, the classification loss is computed using the Binary Cross-Entropy Loss (BCELoss). In this project, the network predicts the probability that each anchor box contains a nodule. This probability is compared against the ground truth labels and the BCELoss is calculated accordingly.

Regression Loss: Because the model doesn't just classifies if the nodule exist or not but it also detects the location of the nodule, the regression loss is used. The regression loss focuses on refining the predicted bounding box coordinates to better match the ground truth box locations. It is computed using the Smooth L1 Loss.

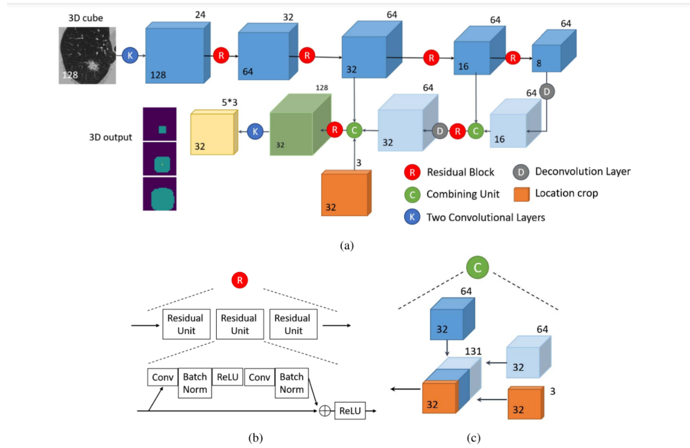

Figure 4 3D CNN Design [15]

V. Experimental Results

In this section, by using measurement metrics such as IoU and confusion matrix the success of the segmentation is evaluated

A. 3D CNN IOU Result

When measuring success in the segmentation task the IOU metric is highly used . The IOU demonstrates how much real mask and predicted mask overlap. After training with learning rate 0.001 for 50 epoch, IOU is calculated as 0.7.

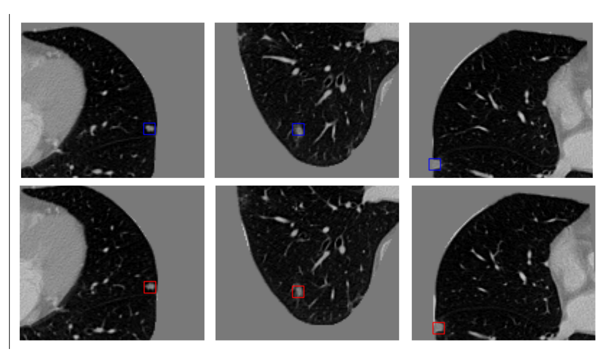

Figure 5 Detection Comparison

B. 3D CNN Confusion Matrix

A confusion matrix is a representation that is used to evaluate the model performance in terms of classification. It displays the predictions' summary by comparing them to the actual ground truth labels. When the trained 3D CNN model is tested on 20 ct scan the following result is observed.

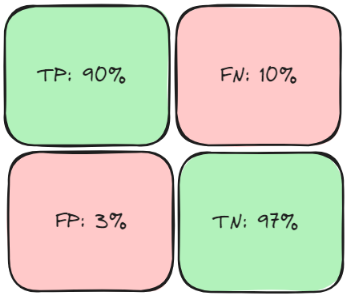

Figure 6 Confusion Matrix

VI. Application

A. Web UI

A website UI is created to interact with clients. The website is responsible from getting the ct data from the clients and sends it to the server. The server is responsible from the preprocessing the ct scan and detection of the lung nodules. The website is designed with html,css and js and the server side is handled by python's flask library. The trained 3D model is responsible from the detection task .

The CT scans should be sent in a zip file that contains the mhd and raw file format.

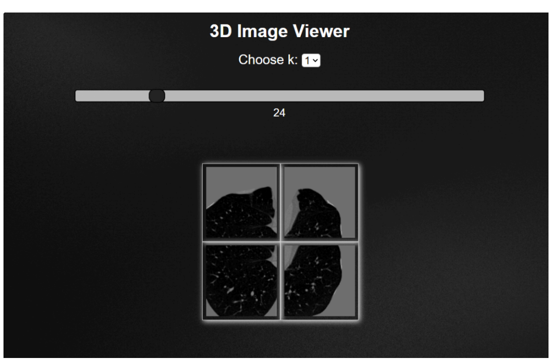

Figure 7 Website UI

VII. Performance Analysis

A. Model Training Performance Analysis

Deep learning models needs powerful GPUs. The dataset used for the training was quite huge. Therefore a powerfull GPU and RAM is needed. Therefore Google Colab is utilized with L4 GPU because of its high capacity and and 52GB RAM. Below the RAM usage, GPU usage and disk usage are demonstrated.

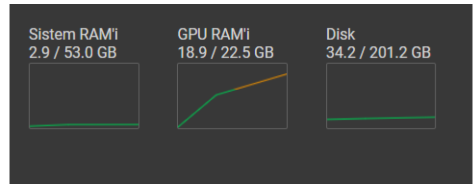

Figure 8 Model Training Performance

B. Preprocessing Performance Analysis

The preprocessing takes a lot of time due to the heavy processing load of the 3D scan. It iterates over the ct scan and apply preprocesing to every slice. The performance of the preprocessing is shown below in terms of time.

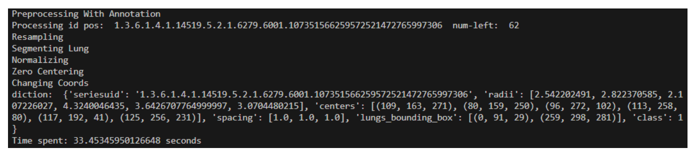

Figure 9 Preprocessing Performance

C. Model Performance Analysis

The detection with the trained model performance is tested by observing the success and the time it takes to finish detection. The performance analysis can be seen below. The model performance is tested with i7 CPU and 16GB RAM.

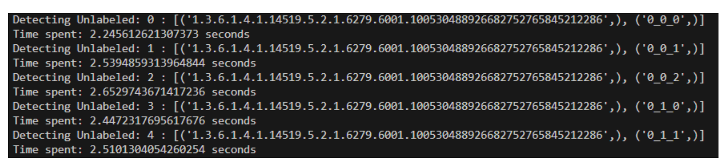

Figure 10 Model Detection Performance Analysis

VIII. Conclusion

This Project aims to provide an effective solution to detection of early-stage lung cancer from low-dose CT scans. Comparing to high dose CT scans, low dose CT scans provides less risk and lower radiation exposure. However, it also decreases the scan quality and its readability. Therefore, preprocessing methods and deep learning techniques are used to enhance the scan quality and detect the nodules that might turn into cancer. Specifically engineered 3D CNN is utilized for the detection of the lung nodule. The model successfully detects the nodule location and classifies it as a nodule.

A web-based UI is also developed. It gets the ct scans as input and provides an enhanced image and detection result. The ct scans gotten from the UI sends back to the server. The server preprocess the image and provides a detection result that is gotten from the model. The result is sent back to the UI so the doctors can make sense of it and provides needed medical treatment to the patient.

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