Volumetric CT Scan Analysis for Pulmonary Nodule Detection and Malignancy Classification Using 3D CNN Architectures

J. Ravindra Babu[1], B. Sandeep Raghavendra[2], A. Jaswanth kumar[3], G. Vignan[4], J. Ganesh[5], K. Madhu[6]
[1]Assistant Professor, Dept. of CSE–Data Science
KKR & KSR INSTITUTE OF TECHNOLOGY AND SCIENCES
GUNTUR
Email: jravindra7@gmail.com
[2,3,4,5,6]B. Tech Student, Dept. of CSE–Data Science
KKR & KSR INSTITUTE OF TECHNOLOGY AND SCIENCES
GUNTUR
Emails: bsandeepr54@gmail.com, jkamaralpudi@gmail.com, vignangera07@gmail.com, ganeshjakka665@gmail.com, kattamadhu718@gmail.com

***Abstract*—Lung cancer is a reason why a lot of people die from cancer all over the world [1]. If doctors can find lung cancer early then people are more likely to survive lung cancer [1]. Doctors usually look at pictures from a CT scan. They use it to check for lung cancer [2]. The pictures, from the CT scan help doctors see what is going on inside the body. They can then check these pictures for lung cancer [2]. People also use a type of computer program called a 2D CNN (Convolutional Neural Network) to help them find lung cancer. They use this 2D CNN to look at pictures and find lung cancer. The 2D CNN is very good at helping people find lung cancer. This project is about creating a computer program that can find and sort out lung cells these lung cells are called nodules. The program uses 3D Convolutional Neural Networks (or) 3D CNNs to do this [1]. This project is about looking at the lung scan all at once instead of looking at one part of the lung scan at a time. The program looks at the lung scan, which is made up of lung nodules and it tries to find all of the lung nodules, in the lung scan. The thing about lung scans is that they can be really hard to read [1] [2]. That is where 3D CNNs come in. They help the program look at the lung scan. Find the pulmonary nodules. 3D CNNs look at things in three dimensions. They use units of information called voxels [1]. Voxels help get a picture of what the bad cells look like. The 3D approach is useful because it helps us see the shape and texture of the cells. It also shows us where the cells are located in the lung. This project uses 3D CNNs to make all of this happen. The 3D CNNs are what make it possible to get a better look at the lung scan and find the pulmonary nodules. The 3D CNNs are really good at helping us understand the cells in the lung. The 3D CNNs are very helpful when it comes to the cells, in the lung [1].**

The way we do things has three parts:

1. Preprocessing: Normalizing and segmenting lung volumes from the LIDC-IDRI / LUNA16 dataset to focus on the area of interest (ROI) [6]. 2. Nodule Detection: Using a 3D Region Proposal Network (RPN) or 3D U-Net to find potential nodule locations [1]. 3. Classification: Implementing a 3D CNN classifier (e.g., 3D ResNet or C3D) to label detected nodules as benign or malignant based on malignancy probability scores [2].

The main goal of this project is to create a computer system that can help doctors diagnose problems [1]. This computer system is called a computer-aided diagnosis system. The computer-aided diagnosis system should be better than looking at pictures of the body one slice at a time.

***Index Terms*—Lung Cancer, 3D CNN, Pulmonary Nodules, Volumetric Analysis, Deep Learning, LUNA16, Medical Imaging.**

I. Introduction

Health is the one of the important aspect in the life. Now a days many health problems are taking place in the human body due to various causes [14]. One of the major health problem is in the lungs & heart [14]. As the heart plays the main function in the human body, the lungs are very important for the supporting of the heart [1]. If some problem is occurs in the lungs then it may cause huge lose to the human [1]. In order to overcome the huge lose, modern technology came with a terrific solution known as "CT scan"

The Computed Tomography scan which is shortly known as CT scan is a medical imaging technique used to get the detailed internal images of the body. This is one of the advanced technique in the medical field used to treat the patients [1]. The person who perform the CT scan are generally known as radiographers. The CT scan is done for the several parts of the body like head, chest, abdomen, bones.

The CT scan is done to get a detailed information of bones, organs, and soft tissues in the form of images to diagnose injuries, diseases, conditions and to guide procedures like surgery [1] [14]. This is fast and effective for the emergencies and for the monitoring treatment progress.

The reasons & purposes for doing the CT scan are tumors, cancers, brain issues, abdominal issues, chest problems, bone & spine problems, vascular conditions, and many more [1] [14]. Before the invention of the CT scan is it highly impossible to detect the problem occurred. With the help of the CT scan we can breakdown the difficulties of the detection of the problem and the process of the curing the problem.

Here by the usage the CT scan the medical field overcomes the major problems faced in the pulmonary [1].

II. Problem Statement

A 2D CT scan system usually works with pictures from computed tomography scans. The 2D CT scan system is not always accurate. It has trouble reducing artifacts. The 2D CT scan system also has a time putting all the pictures together for a full volumetric analysis.

In imaging like when doctors look for pulmonary nodules the main issue is looking at 2D slices to find and classify potential malignancies. The doctors have to deal with noise, low contrast and variations in quality. This makes it hard to detect problems on without using advanced processing, for the 2D CT scan system.

A. Key Challenges

When we look at 2D slices it is hard to see things because we do not have a good sense of depth. This makes it tough to tell overlapping structures or small nodules apart from the tissue that's, around them. We have trouble seeing the nodules because they are surrounded by tissue that looks similar. The overlapping structures are also hard to distinguish in 2D slices.

Things that are not supposed to be in the image like artifacts from beam hardening or when the patient moves or when the system has errors make the image not look as good as it should. This means that doctors cannot rely on the image to make a diagnosis. Artifacts from beam hardening, motion or system errors are a problem because they reduce the quality of the image and that is not good, for diagnostic reliability of the image.

Doing things by hand takes a lot of time. People can make mistakes. So we need to use computers to do the work for interpretation because manual interpretation is not good for looking at a lot of things. This way manual interpretation can be done faster. With fewer errors, for manual interpretation.

III. Literature Review

People who study literature about using computers to look at volumetric CT scans for finding lung problems are saying that things are different now [2] [3]. The fact that 3D computers are able to help us understand lung problems. This 3D computers explains lung problems better than 2D computers. So 3D computers are very helpful when it comes to understanding lung problems.

At first people were trying to teach computers what to look for. They were not very good at it. After 2015 people started using sets of data, like LIDC-IDRI and LUNA16 to teach computers to look at volumetric CT scans and find lung problems on their own [4]. Now these computers can find most of the lung problems than 90 percent of the time which is very good [2] [3].

Lung problems are found by computers using volumetric CT scans. This is a big improvement. These studies tell us that we need to use computer programs like 3D CNNs to find problems with the lungs.

We have to build these 3D CNNs so that we can use them to find problems with the lungs [1] [15].

We need to use 3D CNNs to help doctors find problems, with the lungs. When we create the 3D CNNs we have to consider a lot of things. This is how we can find things like nodules. The 3D CNNs are useful because they help us avoid saying that something is bad when the 3D CNNs know it is really fine [1] [5]. We use the 3D CNNs to make sure we get it right. The 3D CNNs are important for this.

The 3D CNNs are really good for this type of work. We should use the 3D CNNs to look at things from angles. This will help us find the nodules [1].

A. Early Developments (Pre-2018)

The first time that the 3D CNN was used was for things like the work that Setio et al. Did, in LUNA16 [4].

They used the CNN to find things in the 3D pictures.

They used a combination of 2D pictures and 3D pictures to get rid of positives by looking at the 3D CNN results from many different angles [4]. This way they could see the 3D CNN results from lots of sides. The 3D CNN results were looked, at carefully to make sure they were correct. They used the 2D pictures and the 3D pictures together to check the 3D CNN results.

This method was really good, for the CNN and the 3D CNN got a very good score of 0.923 on LUNA16 when they used the 3D CNN [4]. The 3D CNN did a job and that is why the 3D CNN got such a good score.

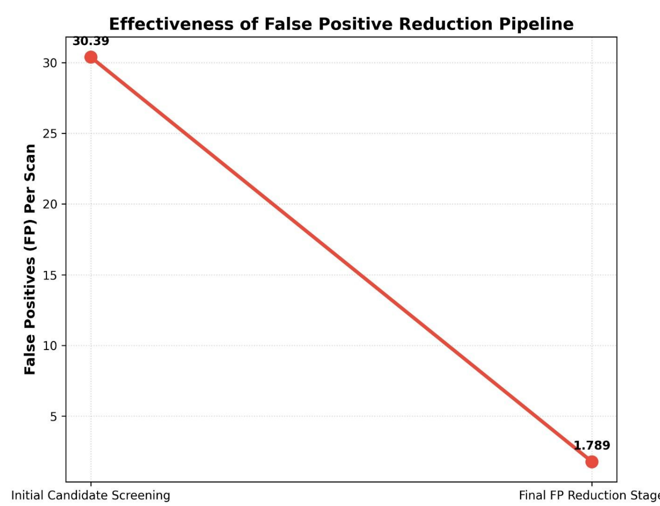

Fig. 1. Visualization of 3D CNN architecture for pulmonary nodule detection

Dou and his team decided to try something with 3D CNN. They looked at parts of pictures like tiny sections that are 40x40x26 [10]. He and his team used ways to look at these tiny sections of pictures. This really helped him. His team make their 3D CNN much better at finding things in pictures [10]. Dou and his team were able to get a score of 0.827 with their CNN. He and his team were happy, with what they found out about 3D CNN. I think the new ways of using 3D CNN are really good. 3D CNN is better than the ways that did not use deep learning [10].

B. Key Architectures And Advances

3D ResNet, U-Net variants, and Inception-based models dominate, with innovations like Res2SENet for multi-scale features (sensitivity 0.923 on LUNA16) [8] and attention mechanisms boosting AUC to 0.93 [8]. Multi-task learning (e.g., PN-SAMP by Wu et al.) jointly predicts segmentation, attributes, and malignancy (97.58% accuracy on LIDC-IDRI). Ensembles like DeepLung [5] integrate detection and classification via 3D dual-path networks [5].

IV. Proposed Systems

The research paper presents an implementation of a computer-aided diagnosis (CAD) system to detect and classify pulmonary nodules using volumetric CT scans from the LIDC-IDRI and LUNA16 dataset. The approach advances 2D methods by utilizing 3D CNNs to provide a more complete description of nodule characteristics, such as shape, spatial context, and texture, based on voxels.

Three stages comprise the system processing: 1.Preprocessing - The preprocessing stage normalizes the CT image data into a common range of Hounsfield Units (-800 to 200 HU), clips the voxel values between -4 and 1, and segments the lung volume into regions of interest (ROIs) around each nodule (e.g., a voxel cube with dimensions of either $32 \times 32 \times 16$ or $16 \times 16 \times 16$ that has a 20% padding) based upon the center line of the nodule. Any nodule measurement that is grossly over 3 mm will be automatically separated into its ROI; if the measurement is unclear then a KNN labelling method will be applied. 2.Nodule Detection - The nodule detection uses either a 3D Fully Convolutional Network (FCN), Multi-Scale 3D CNN (e.g., patches of $20 \times 20 \times 6$ / $30 \times 30 \times 10$ / $40 \times 40 \times 26$), or a 3D Region Proposal Network(RPN)/3D U-Net by generating candidate ROIs for available detected nodules with the aim of reducing the number of false positive results. 3.Classification - In classifying nodules as benign/malignant, 3D CNN Classifiers (e.g. 3D ResNet, C3D) determine assigned malignancy labels through reading combined deep features (e.g., 64-D vectors) and Radiomics (e.g., Volume, Surface) and combine these into a Random Forest or SVM/NN ensemble to make determination of malignancy probability.

V. Methodology

The doctor uses a kind of scan called a Volumetric CT scan to look at lung nodules and figure out if they are bad or not. This scan uses a type of computer program called 3D CNN architectures to look at the picture not just a small part [1]. This way it can see things that other methods might miss.

To do this the doctor first gets the ready then finds the nodule or cuts it out. Next the computer looks really closely at the nodule. Tries to learn more about it. Finally the computer says if the nodule is benign or malignant [1] [2]. The doctor uses a different ways to make sure they get it right like combining the computer program with other tools like radiomics and biomarkers [15]. This helps the doctor make an accurate decision, about the Volumetric CT scan and the lung nodule.

A. Data Preparation

We use CT scans from datasets like LIDC-IDRI [6]. First we take these CT scans. Get them ready to use. We do this by cutting out the parts from the CT scans. These parts are the areas that're important to us, which we call CT scans regions of interest. We usually find these CT scans regions of interest, around nodules. We look for CT scans regions of interest because they help us understand the CT scans better [6].

We use cubes to do this. The cubes are usually 32x32x16 (or) 16x16x16 voxels, in size [6]. We put the center of these cubes on the centers of the nodules that we know about. Then we add some space around the nodule. This extra space is usually twenty percent of the size of the nodule [6]. We do this with the cubes.

Now we look at the values of the pixels in the CT scans. We change these values into something. We change these values into Hounsfield units [6]. Then we check the Hounsfield units to make sure they are just right. We do not want the Hounsfield units to be too high or too low. So we make sure the Hounsfield units are, between -800 and 200 Hounsfield units [6]. This way the Hounsfield units are good to use.

We need to make these values normal. This is because the values have to be steady and okay for training. The values are made to be between -4 and 1 [6]. This is done to the CT scans from the LIDC datasets. Nodules that are 3mm or bigger are separated automatically. The ones that are not completely sure are left out so that we can say if they are benign or malignant.

Sometimes we use a method called KNN to label them when we are not really sure so that we can use them for training too [3] [4].

B. Detection Pipeline

Detection uses a kind of screening that looks at entire CT volumes with something called 3D fully convolutional networks [1] [5]. This helps find areas that might be important which are called candidate ROIs. Then it uses another kind of network called discrimination CNNs to look closer at these areas called volumes of interest to make sure they are not positives.

The detection also uses something called -scale 3D CNNs. These are like tools that can look at things from different distances like 20x20x6 (or) 30x30x10 (or) 40x40x26 [5]. This helps the detection understand what is going on around the areas. It is of like using a special pair of glasses that can see really far or really close.

The detection also uses region proposal networks which're like special maps that help find the exact location of the important areas, in the 3D scans [1] [10]. This helps the detection be very precise and find the spots [1] [10]. Detection uses these region proposal networks on the 3D scan patches to get a good idea of where things are.

C. 3D CNN Architecture

These networks have lots of layers with 3x3x3 convolutions [1] [8]. For example they start with 16 filters. Go all the way up to 512 filters. Networks feature ReLU [1]. Max-pooling with a size of 2x2x2 [1]. They also have connected layers with 1024, 64 and 2 neurons. Networks use dropout with a rate of 0.5 and L2 regularization to prevent overfitting [1] [8].

When you put in volumes like 32x32x32 the Networks can learn everything they need to know from start to finish using stochastic gradient descent [1]. The momentum is 0.9 and the learning rate decays, over time [1]. This way Networks can get really good at what they do with AUCs between 0.73 and 0.80 [1] [8]. Some versions of Networks are even better they add things like attention or ensembles to make them work better [8].

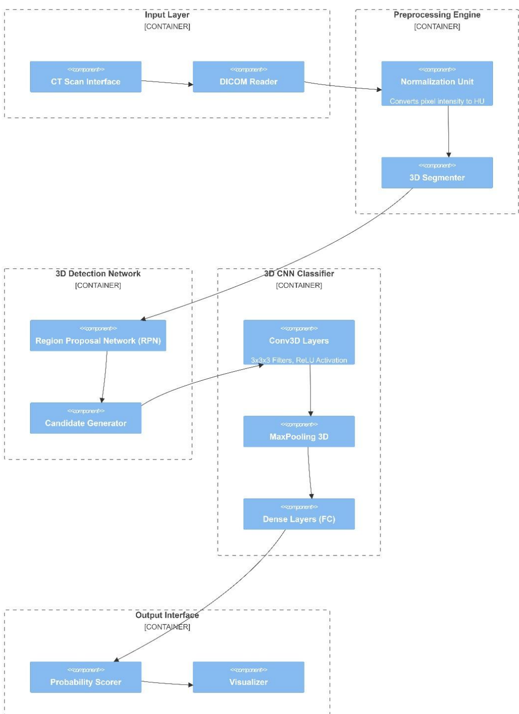

Fig. 2. 3D CNN architecture layers with convolutional and pooling operations

D. Classification and Fusion

When we are trying to figure out if something's malignant we can use a combination of things [2] [15]. We can use computers that look at 3D pictures and find deep features like really small details that are important. These computers can find things like 64- vectors from the layers that are close to the end [2] [15]. We can also use biomarkers which're things like how subtle something is or how pointy it is. We can use radiomics [15], which is like measuring the volume or surface area or diameter of something [15].

We can put all of these things together using something called forests and it actually works better than just using one of these things by itself. For example if we just use biomarkers we get a score of 0.94 [2] [15]. If we use the computers that look at 3D pictures and biomarkers together we get a score of 0.76 [2].

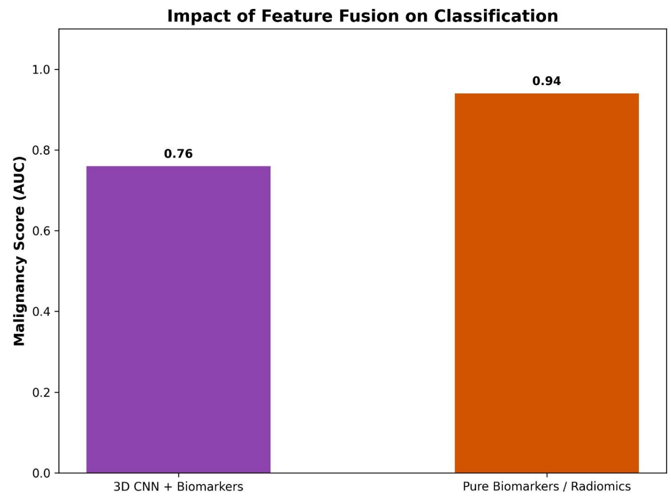

Fig. 3. Fusion of 3D CNN features with radiomics and biomarkers for malignancy classification

We can also use these computers with models like SVM or NN and use features that we have carefully chosen. When we do this we can get better scores, like 0.78 to 0.80 by using a second stage of classifiers [2]. This means that malignancy classification, which is what we are trying to do can be more accurate when we use all of these things together. Malignancy classification is, about finding out if something is malignant and using all of these tools can help us do that.

E. Evaluation Metrics

Five-fold cross-validation on balanced datasets (e.g., 326 pathologically confirmed nodules) reports ROC AUC (0.70-0.94), sensitivity (90%) [7], Dice (0.80 for segmentation), with DeLong tests for significance (p¡0.05) [7]. Semi-supervision via KNN on intermediates enhances training data [3] [7].

VI. Result

Doctors can now find lung problems easily with the help of computer programs. These computer programs look at CT scans in a way using something called three-dimensional convolutional neural networks or 3D CNNs [1] [2].

The old way that doctors used to do things was to look at pictures one slice at a time.

3D CNNs look at the lungs as a whole three-dimensional thing [1] [2].

This means that 3D CNNs can see each spot in the lungs from angles.

They can see the shape of the lung spot and the edges of the lung spot [1] [2].

3D CNNs are really good, at finding lung problems because they look at the lung. What is inside the spot. The doctors can see what is going on with the lungs. Find problems accurately. Lung problems can be found with the help of these computer programs and 3D CNNs. This is really helpful for the doctors to understand what is going on with the lungs.

The special computer programs and 3D CNNs are very good, at detecting lung problems.

The 3D CNN systems can find lung nodules 90 percent to 98 percent of the time [1] [2] [12].

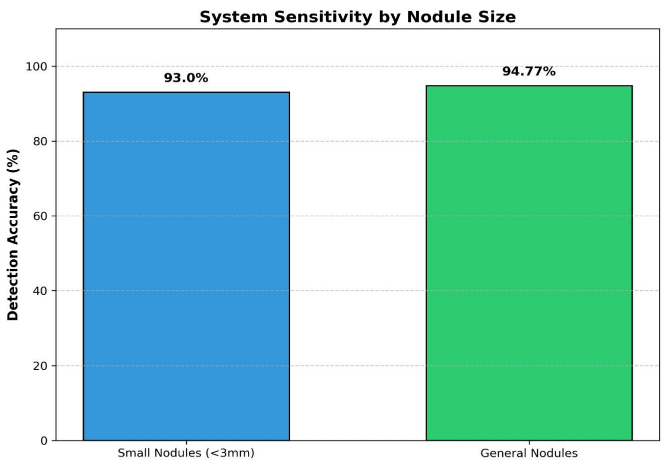

Fig. 4. Comparison of 2D vs 3D CNN performance in pulmonary nodule detection

The 3D CNN systems can tell the difference between lung nodules that're not harmful and lung nodules that are cancerous because the 3D CNN systems are able to look at lung nodules in a lot of detail [2] [12].

The 3D CNN systems are good at finding lung nodules and the 3D CNN systems are good, at telling us if the lung nodules are bad or not.

The 3D CNN systems work in a way that's similar to how doctors look at pictures from CT scans. Doctors use these pictures to see what is going on inside the body

When doctors combine their medical expertise with these AI tools, diagnoses become even more reliable [2] [14]. The collaboration between humans and machines enables faster and more confident decisions about whether a nodule is malignant or benign [2] [14]. Overall, 3D CNN–based volumetric CT analysis represents a major advancement in computer-aided diagnostics, improving early lung cancer detection, patient outcomes, and the efficiency of radiology workflows [1] [2] [14].

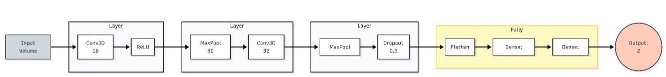

Fig. 5. Clinical workflow integration of 3D CNN-based pulmonary nodule analysis

VII. Discussion

The Volumetric CT scan analysis is really good at helping us understand what is going on inside the body especially in the lungs when we use it with something called three-dimensional convolutional neural networks or 3D CNNs for short [1] [2] [14]. These 3D CNNs are better than the way of doing things with two-dimensional models that only looked at one picture of a CT scan at a time.

The 3D CNNs look at the lung volume, in three dimensions, which is a big improvement [1] [8] [14].

This means the Volumetric CT scan analysis and the 3D CNNs can see everything that is happening in the lungs [1] [8] [14]. This helps doctors get a good look at lung nodules. They can see the shape of lung nodules the texture of lung nodules and what's inside lung nodules. This is important because it helps doctors find problems, like lung cancer. Doctors can find lung cancer when it is still early which is really good. Lung cancer is a deal so finding lung nodules and understanding what they are is crucial for doctors to detect lung cancer [1] [8] [14].

3D convolutional neural networks are really good at finding lung tumors. Figuring out if they are bad or not [1] [2] [8]. These computer models can look at pictures from sets like LIDC-IDRI and get it right most of the time.

Because 3D convolutional neural networks can learn from a lot of CT pictures they can find patterns and problems on their own with little help from people [2] [6].

This means there are mistakes and doctors can focus on the important pictures instead of looking at every single one by hand [2] [6]. Three dimensional convolutional neural networks are very helpful, in this way.

In care using 3D CNN analysis along with what doctors know and other health signs makes a very good system for figuring out what is wrong with someone [1] [2] [14]. The computer programs give results that're not biased and are based on the numbers and doctors add their medical knowledge to make sure the diagnosis is correct and to make it more precise [2] [14]. Overall, volumetric CT with 3D CNNs represents a major advancement in medical imaging, improving both the quality of diagnosis and patient outcomes in lung disease management [1] [2] [8] [14].

VIII. Expected Outcomes

- Detection performance
- Classification accuracy
- Clinical impact
- End-to-End Diagnosis
- Superior 3D context

IX. Conclusion

The paper presented a conceptual design for a better CT scan by using the 3D CNN [1]. 3D CNN architectures are really good at analyzing volumetric CT scans to find nodules and figure out if they are bad or not. They do this by using the 3D spatial context [1] [**?**]. This means they are better than 2D methods and a lot of other systems that came before them

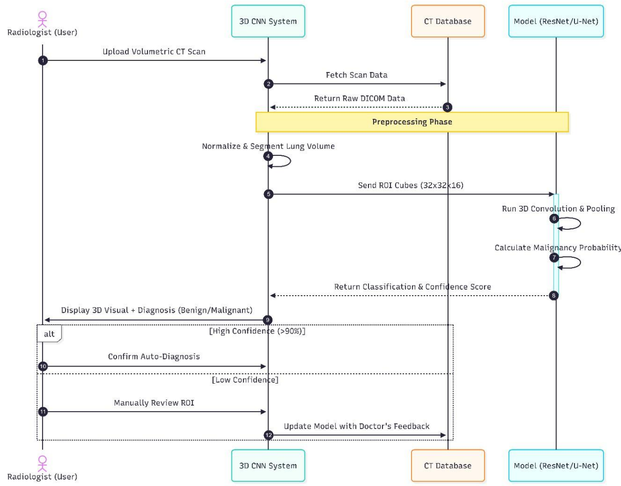

Fig. 6. 3D visualization of pulmonary nodules detected by the proposed system

[1] [8] [14]. 3D CNN architectures can look at things in a way that's more like how we see the world, which helps them make better decisions, about pulmonary nodules.

These systems are really good at finding things [1] [8] [14]. They can detect things correctly about 94.77 percent of the time [12]. Sometimes they make mistakes. Say something is there when it is not [12]. This happens about 30.39 times per scan when they are looking for candidates [12]. They get a little better at not making mistakes. Only do it about 1.789 times per scan when they are trying to reduce false positives [12]. Overall these systems can detect things about 89.29 percent of the time [12].

The systems also do well in competition. They get a score of 0.8135 on the competition performance metrics [12]. This is better than methods, like ensemble methods that get a score of 0.722 [12].

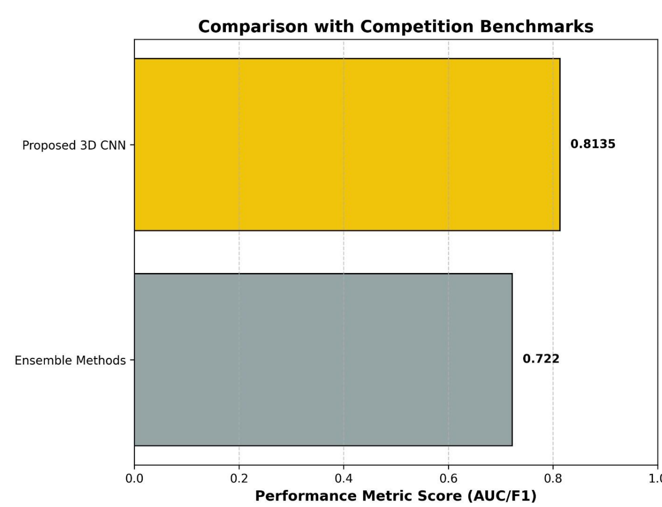

Fig. 7. Performance metrics comparison of proposed 3D CNN system with existing methods

These models help doctors find lung cancer by looking at low dose CT scans for lumps [1], which makes the doctors job easier and reduces mistakes [1] [13] [14]. They follow rules like the ones from the Fleischner Society [13]. They can even find very small lumps that are less, than 3 millimeters big, which is really good because they can find almost all of them about 93 percent of the time so doctors can keep an eye on them [13].

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