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Classification of Suspected Pulmonary Nodules Based on AI Approaches

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Abstract

Our research is focused on utilizing artificial intelligence techniques to classify pulmonary nodules, with the goal of improving diagnostic accuracy and efficiency. By employing sophisticated models, we aim to provide automated analysis of pulmonary nodules, enabling early detection of lung pathologies and enhancing patient care.

To achieve this, we have developed a ground breaking approach that starts with pre-segmented 3D CT scans of nodules. From these scans, we extract three meticulously crafted 2D images representing the nodule from different perspectives: x, y, and z views. Taking inspiration from the pioneering work of G. Hinton [1] which was further improved by Sara Sabur et al in 2017 [2], our methodology revolves around the implementation of capsule networks. As a result, we have created three specialized models, each tailored to a specific view.

In cases where there is disagreement among the three models, we employ three basic methods for final classification: strict classification, majority classification, and threshold-based classification. Furthermore, we have incorporated game theory principles to determine the category of the nodule (benign or malignant).

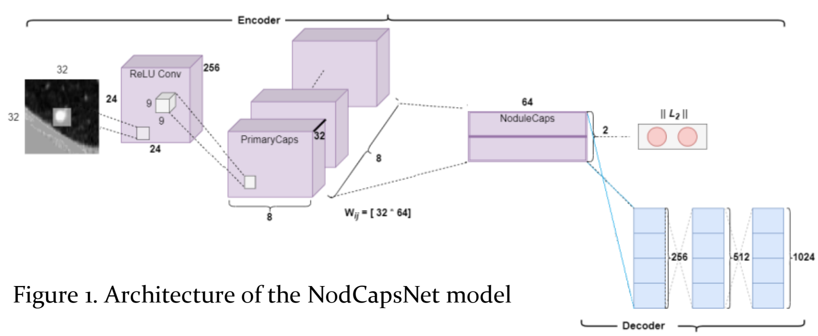


Figure 1. Architecture of the NodCapsNet model

1. Introduction

Our research uses AI techniques to classify pulmonary nodules for improved diagnostic accuracy and efficiency. Our groundbreaking approach starts with pre-segmented 3D CT scans, from which we extract three 2D images representing the nodule from different perspectives. Our methodology revolves around the implementation of capsule networks, resulting in three specialized models tailored to specific views. We use three basic methods for final classification and incorporate game theory principles to determine the nodule's category.

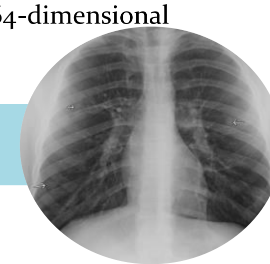
2. Method

2.1. NodCapsNet Model

The dataset used to train and test our neural network is the "Data Science Bowl 2017" dataset, abbreviated as DSB2017 [3]. The dataset consists of approximately 753 segmented nodules of size (64*64*64).

a) Encoding:

The encoder plays a crucial role in transforming a 32x32 pixel image of a nodule into a 64-dimensional instantiation parameter vector that encapsulates essential nodule information.



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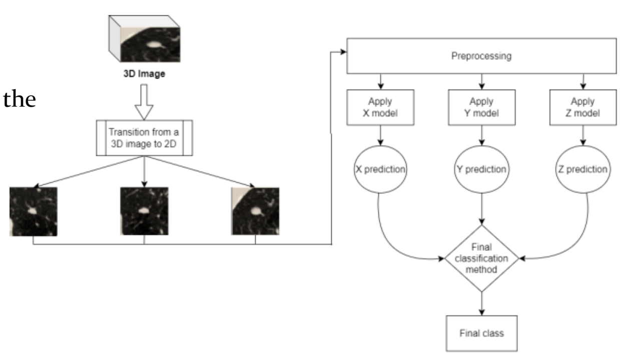
The convolutional layer is responsible for detecting basic features in the input image using 256 kernels of size 9x9. The primary capsules, eight in total, each apply 32 kernels of size 9x9x256 to detect specific nodule features such as size, texture, and orientation.
The NoduleCaps layer consists of two capsules of size 64. This layer encodes not only the activation of features but also the spatial relationships between these features.
The capsules then generate output vectors specific to different nodule classes, such as "benign" or "malignant," by utilizing vector output norms and the squash function.

b) Decoding:

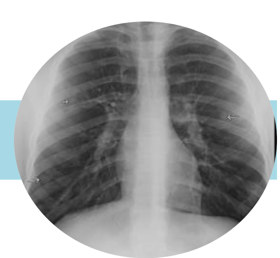
After encoding, the decoding process is necessary to encourage the capsules to select the most relevant features.
We apply deconvolution layers to progressively enlarge the vector representation and restore the spatial features of the image.
Our goal is to generate a reconstructed image that closely resembles the original image, with the Euclidean distance serving as the loss function. The closer the reconstructed image is to the input image, the better the decoding process.

Figure 2. General diagram of the classification system



c) Integration of Gabor Filter:

The Capsule Network model for pulmonary nodule classification has been enhanced through the integration of the Gabor filter [4]. In standard capsule networks, visual features are learned automatically from the input data, limiting the ability to explicitly select features like size and orientation. By incorporating the Gabor filter, originally developed for tasks such as edge detection and texture analysis, the network gains the ability to capture more relevant visual attributes from the nodule images. The Gabor filter operates by convolving the input image with specific kernels designed to extract spatial frequency, orientation, and phase information. This integration allows the capsule network to capture subtle patterns and variations in the nodules, leading to improved classification accuracy and performance.



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2.2 Classification system

Phase 1:
The system takes a 3D image (646464) of a segmented pulmonary nodule from a lung CT scan as input. To optimize the classification process, we select the central slice for each view axis. This reduces complexity and speeds up the training process.

Phase 2:
In the second step of our system, we apply preprocessing techniques to our 2D images, such as intensity normalization, resizing, and Gaussian filtering to reduce noise. These processed images are then fed into our pre-trained model to generate predictions.

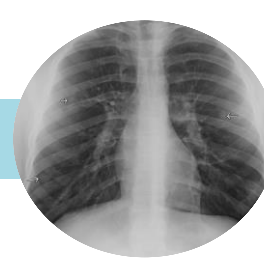
Phase 3:
The final phase of the system involves making a conclusive decision about the nature of the input nodule based on the three predictions obtained in Phase 2. To achieve this, we employ a final classification method.

Final Classification Methods

<u>Majority Classification:</u>
The class that is predicted most frequently by the three models is selected as the system's final decision.
<u>Strict Classification:</u>
If at least one of the models predicts a malignant class, that class is returned as the final decision.
<u>Threshold-based Classification with Coefficients:</u>
The predictions of the three models are weighted with coefficients, where the model with the highest accuracy has the highest coefficient. Their average is then compared to a threshold calculated during the training process.
<u>Game Theory Classification:</u>
The system creates a zero-sum game where it confronts the views as players, and their strategies are the features calculated from a set of reference images.
In our game theory model, we have utilized the following features: energy and homogeneity from the co-occurrence matrix, as well as Hausdorff distance and spectral radius.

3. Experimental Results

Excluding the Gabor filter led to a decrease in loss but a low precision rate. However, incorporating this filter significantly improved the precision rate of the model across all three viewing angles, achieving a minimum of 92%. Furthermore, enhancing the number and size of primary capsule vectors yielded better outcomes with fewer iterations, thereby reducing the duration of training (see table 1).
Based on these findings, we have chosen NodCapsNet32 as the deep learning model for our application.



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The majority voting method had the highest precision rate, as all three models had high accuracy for the viewing angles they were trained on. The thresholding model also produced good results due to the calculation of credible thresholds during training. This approach improved the overall performance of the model by using reliable thresholds for calculating prediction averages.

Using game theory, we achieved satisfactory results by utilizing features of lung nodules from a set of pre-selected reference images, with a prediction rate of 85%. However, it is important to note that the similarity between nodules can affect the results, as a benign nodule may have similar characteristics to a malignant one. For the strict method, forcing the models to agree did not help with decision-making, as a model trained on one view may interpret the nodule class differently.

Model	Parameters, Metrics and Results											
	Iter	m_+	m_-	λ	α	Nb_Prim_Caps	T_Prim_Vec	T_Sec_Vec	Routing	Gabor	View	Loss	Accuracy
NodCapsNet	50	0.8	0.5	0.9	0.001	32	32	64	5	no	X	0.3	44%
										no	Y	0.23	48.1%
										no	Z	0.225	48.33%
NodCapsNet8	100	0.8	0.5	0.9	0.001	8	32	64	5	yes	X	0.0207	93.49%
										yes	Y	0.4652	92.43%
										yes	Z	0.0169	93.49%
NodCapsNet32	50	0.8	0.5	0.9	0.001	32	32	64	5	yes	X	0.0213	94.1%
										yes	Y	0.02	92.56%
										yes	Z	0.017	94.28%

Table 1. NodCapsNet model results

Method	Accuracy
Majority	96.67%
Strict	92.96%
Thresholding	95.08%
Thresholding + Coefficients	95.48%
Game Theory	94.55%

Table 2. Results of classification methods

References:

[1] G. E. Hinton, A. Krizhevsky S. D. Wang , Transforming Auto-encoders, University of Toronto. http ://www.cs.toronto.edu/ fritz/absps/transauto6.pdf
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