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Thyroid Nodules Classification in Medical Ultrasound Images using Deep Learning

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Abstract*: Ultrasound scanning is most excellent significant diagnosis techniques utilized for thyroid nodules identification. A thyroid nodule is unnecessary cells that can develop in your base of neck which can be normal or cancerous. Many Computer added diagnosis systems (CAD) have been developed as a second opinion for radiologist. The thyroid nodules classification using machine learning and deep learning approach is latest trend which is using to improve accuracy for differentiation of thyroid nodules from benign and malignant type. In this paper we review the most recent work on CAD system which uses different feature extraction technique and classifier used for thyroid nodules classification with deep learning approach. This paper we illustrate the result obtained by these studies and highlight the limitation of each proposed methods. Moreover we summarize convolution neural network (CNN) architecture for classification of thyroid nodule. This literature review is meant at researcher but it also useful for radiologist who is interesting in CAD tool in ultrasound imaging for second opinion.

Keywords: CAD system, CNN, Malignancy, Thyroid nodules, Ultrasound imaging.

I. INTRODUCTION

Thyroid is a very fundamental butterfly molded organ which is situated before neck. For effective activity of the human body, thyroid gland plays a very important task which produces fluid thyroxine (T4) and tri-iodothyronine (T3) hormones [1]. Thyroid regulates metabolism, and complete growth of the human body and ultimately the development of the brain [2]. But any hormonal imbalance creates a thyroid problem which later leads to thyroid nodules. Thyroid knob is an unnecessary cell development in thyroid organ which can be kind or dangerous. More than 50% of the adult population may have problem of thyroid nodule. Actually the cancerous thyroid nodules are of 7 % only, hence for detecting that small no of cancerous nodules from normal there is a need for development of automatic, accurate thyroid nodules diagnosis system [3].

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The preliminary thyroid disease can be diagnosed with the help of normal blood test which shows thyroid stimulating hormone (TSH) [4], T4, T3 level which will give the information about working of the thyroid gland whether condition is normal or hypothyroidism or hyperthyroidism[5][33]. But later for thyroid nodules, the verities of diagnostic methods such as Elastography, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), ultrasound imaging, Computed Tomography (CT) scan Radionuclide Imaging are available. Out of these, ultrasound imagining is widely used because of its low cost, no ionizing radiation, and high sensitivity [6]. Different classes of the thyroid nodule can be found by analyzing ultrasound image by cervical lymph, nodes size, border, calcification, echoes texture. Evaluation of thyroid nodules depends on radiologist experience and the ability to find subjective details of nodules because benign and malignant nodules having same internal characteristics. So finally doctors suggest fine needle aspiration (FNA) biopsy[7][8] techniques for proper diagnosis of nodular lesion, but all the time FNA biopsy test is not feasible to categories nodules in benign and malignant. To avoid FNA biopsy test many researchers have developed the CAD methods to classify the thyroid nodules.

Basically, computerized diagnosis of any disease framework comprises of stages like denoising, image segmentation, attribute extraction and classification. CAD system did the feature extraction of thyroid nodule like mean, variance, histogram, intensity difference etc.[9]. Moreover, hybrid features like Local Binary Patterns (LBP), Histogram of Oriented Gradient (HOG) and can be used [10]. In classification stage variety of classifier are used like K-nearest Neighbors (KNN), Support Vector Machine (SVM)[11][12], Probabilistic Neural Network(PNN), Deep convolution neural network (DCNN)[13].

In the literature many works has been attention on feature extraction and different classifier. Esin Dogantekin, Akif Dogantekin, Derya Avci c, uses Generalized Discriminate Analysis (GDA) for feature extraction and uses SVM classifier. Experimental analysis shows that there is 91.8 % of accuracy, but the limitation is it diagnosis only thyroid disease and not considered thyroid nodules. [5]. In this paper authors extract feature like Coefficient of Local Variation, Histogram Feature, Normalized Multiscale Intensity Difference (NMSID) Feature, and Homogeneity and this system uses SVM, ELM(Extreme learning machine to segment thyroid region. Analysis shows accuracy is 84.78%, 93.56% for SVM and ELM respectively [9].

U R. Acharya, V. Sree S, Filippo Molinari, R. Garberoglio, uses texture based features and uses KNN, PNN classifier gives accuracy, sensitivity, and specificity is 98.9%, 98% , 99.8% respectively[15].Differentiating normal and cancerous thyroid nodules using a technique called Contrast-enhanced ultrasound (CEUS) is described by U. Nemec and authors. Experimental accuracy is 82.6%, sensitivity 76.9% and specificity 84.8% [16]. In the work presented in [17] suggested to extract neighborhood feature and global feature with MIL (Multiple-instance learning) and uses SVM classifier but accuracy is depends on the block size and clustering.
N. Ponraj, Lilly Saviour, Poongodi, M. Mercy uses a watershed segmentation technique and extracted features like mean, variance, entropy, standard deviation. This paper doesn't give detail specification of classified nodules as it's not involved classifier [18] Hashimoto thyroiditis disease identification by ultrasound image explained by S. Kohila and G. Sankara Malliga. In this paper they studied features like, Neighborhood Gray Tone Difference Matrix (NGTDM) Statistical Feature Matrix (SFM), Laws texture energy measures strategies. Classification is done in two groups by two-tailed unpaired T-test and compares results with histopathology. [19] Generally by traditional approach the feature extraction by selecting the essential features and combining different features is a very difficult task so, now a day's convolution neural network (CNN) is coming into the field of medical imaging deep learning. Many advanced CNNs models can catch profoundly nonlinear mappings between inputs and outputs [8]. CNN has two advantages: (1) If there is problem of unusual illumination conditions, camera lens, defocusing, etc., then also automatic detection of important features is possible (2) It is cost effective as the same coefficient is using from image for CNN.

II. DEEP LEARNING BASED CONVOLUTION NEURAL NETWORK (CNNS) ULTRASOUND CAD SYSTEM

This segment we depict Deep learning based computerized diagnosis framework techniques for thyroid knobs identification and classification. The Deep Learning is a new era of the machine learning algorithms uses multiple layer technique to extract higher levels of features. Various types of Neural Networks technologies exist, like fine tuned deep learning network, cascade CNN, but mainly for the image processing task Convolution Neural Networks (CNNs)[20] are used. Figure 1 shows the common overview of thyroid lesions identification system. Figure 2 shows diagnosis system with CNN.[34]

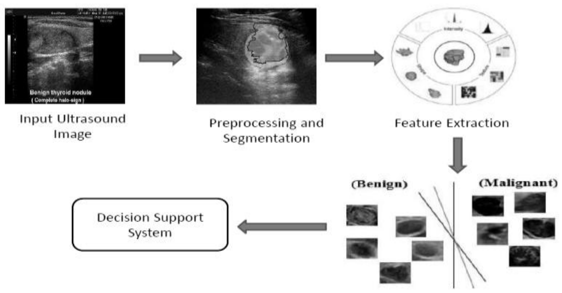


Fig. 1. Common Overview of Thyroid Lesions Identification System

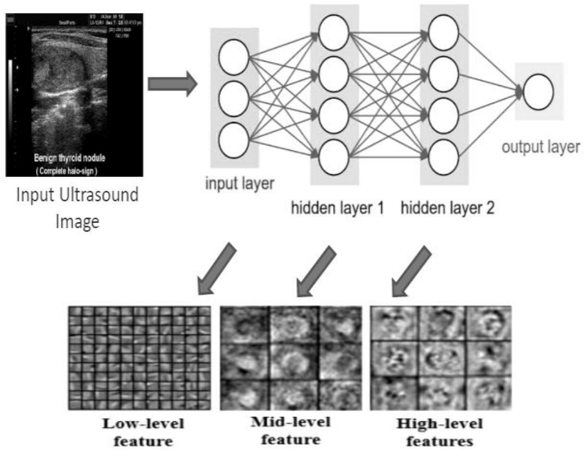


Fig. 2. Diagnosis system with Convolution Neural Network (CNN)

Convolution neural networks (CNNs) are giving dominant performance in image classification and segmentation in deep learning approach than traditional methods [21]. With the help of CNN, fine features are extracted from hidden layer without human involvement, which gives feature map review of detecting features.
In 2016, J. Ma, Fa Wu, Jiang Zhu describes the fusion of two convolution neural network, which fuse the features map of two CNNs which are later trained and fine tuned. In this paper thyroid nodules classification has been done with Softmax classifier with accuracy, Sensitivity & Specificity 83 %, 82.41%, 84.86% respectively[22].The authors made CNN architecture which is trained for sample images to extract simple deep features and fused with HOG, LBP and form hybrid feature map. This paper uses Cost-effective Random Forest classifier with accuracy 93.1%, but author doesn't consider thyroid imaging reporting and data system (TIRADS)[23][24][25][26]score[11].
In addition to this, Tianjiao Liu1 and the team, described fusion of conventional feature with HOG [27][28] and Scale Invariant Feature Transform (SIFT) together to make a feature map for nodule classification with accuracy of 92.9%. Author discussed approach a deep CNN model from image data sets from three hospitals of china, which takes 131731 ultrasound images from 17627 patients with malignant cases which gives an accuracy of 89.8 % [13]. A limitation of this work is it doesn't give sensitivity with respect to tumor size. Yunhua Cao, Ying Fu, and Guang Yang describe feature extraction by sparse representation which gives statistical analysis of the thyroid nodule region and for feature reduction principal component analysis (PCA) for is used. Finally, applied Naive Bayes classifier which gives accuracy 93.3%, the sensitivity 85.1%, the specificity is 98.6% [29].
Authors explained multi scale region based network to extract pyramidal feature for identification of thyroid nodules. And classify it by multi view network where each branch enhances specific group of features which gives an accuracy of 97. 5% [10].
Another CNN approach illustrates multi-task cascade convolution neural network (MC CNN) concept has been used.

The MC CNN framework is made in two layer deep neural network to capture various features. With the help of 4309 ultrasound images it is proven that MC CNN is effective for thyroid lesion detection with accuracy 96%, sensitivity 94%, and specificity of 99.8%. Disadvantages of this research is for nodule size less than 0.01cm and higher than 10 cm, MC CNN gives failure results [30].

In this paper author explain different types of classifiers like, Artificial Neural Network, SVM and Random Forest Classifier. Author utilized autoregressive model for classifying thyroid and non thyroid nodules with accuracy, Sensitivity, Specificity is 90% 92.67%, 97% respectively [31].

III. RESULT AND DISCUSSION OF CNN TECHNIQUES

Following is different CNN technology approach in thyroid nodule classification are summarized which will give idea of CNN architecture in deep learning

Table- I: Performance summary of different CAD systems using CNN.

Author	Feature	Classifier	Performance	Limitations
Jinlian Ma, Fa Wu [22]	Feature mapping of Two CNNs, i.e. one with 9 layers CNN & other with 11 layers CNNs	Softmax Classifier (Fusion of two CNNs)	Accuracy= 83.02 %, Sensitivity=82.4%, Specificity= 84.8 %.	Image data is not sufficient for higher accuracy. We can't exploiting deep CNNs to represent high-level features because of shortage of training sample.
Jianning Chi1 & EktaWalia [11]	Deep learning features	Cost-sensitive Random Forest classifier	Accuracy=99.13% ,Sensitivity=99.70%, Specificity=95.80%.	This study evaluates thyroid nodules into either in class of malignant or benign. They do not categorize nodules with all the TI-RADS.
Tianjiao Liu, Shuaining Xie, [27]	HOG and Scale Invariant Feature Transform (SIFT	Hybrid classification	Accuracy=92%, Sensitivity=90%, Specificity=94.1%.	Accuracy of classifier especially for the malignant cases is less.
Xiangchun Li, S. Zhang, [13]	Two model one is model18 with 50 layers and other the model19 with 19 layers.	Combined deep convolution neural network(DCNN)	Accuracy=95%, Sensitivity=95%, Specificity=95%.	Sensitivity analysis not done with respect to tumor dimension and types of malignant disease.
Yunhua Cao, Ying Fu, and Guang Yang[29]	PCA based Feature selection	Naive Bayes classifier	Accuracy = 93.3%, Sensitivity=85.1%, Specificity=98.6%.	From thyroid ultrasound, manually extraction the accurate image area and found a thyroid lesion is possible those who are having numerous year of experience.
T. Liu a , Qianqian Guo c , C. Lian b [10]	Size, Margine, Shape, aspect ratio,composition ,calcification	Deep-learning based CAD system	Accuracy = 97.1%, Sensitivity=98.2%, Specificity=95.2%.	Image datasets used for evaluating proposed CAD system is not properly balanced that is less benign and more malignant nodules data is used, hence this reduces specificity.
W.Song, Shuai Li. [30]	Local low-level and global high-level features	Multitask cascade CNN framework (MCCNN)	Accuracy =96%, Sensitivity=94%, Specificity=99.8%.	MCCNN gives failure result for the nodules range less than 0.01cm and more than 10cm.
Prabal Poudel ,Alfredo Illanes [31]	Texture of thyroid (segmentation)	Artificial Neural network (ANN)	Accuracy =93%, Sensitivity=92.67%, Specificity=97%.	Using AR model, additional features of US images cannot compute, but it can be done by other methods like Bispectral model.

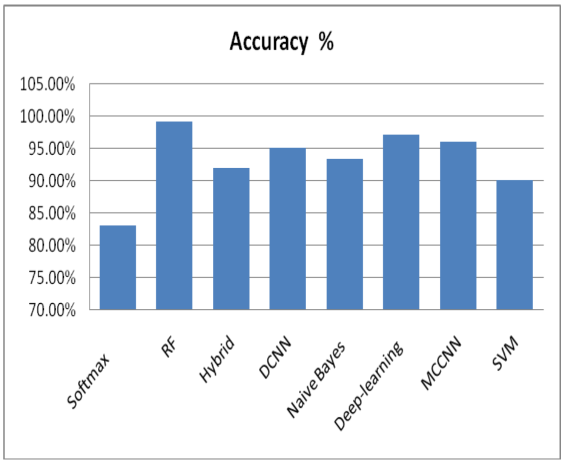
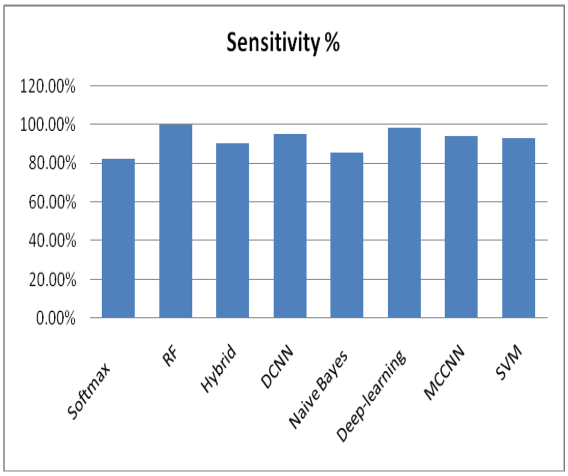


Fig. 3. Comparative Analysis of Accuracy of Classifiers



Fir. 4. Comparative Analysis of sensitivity of Classifiers

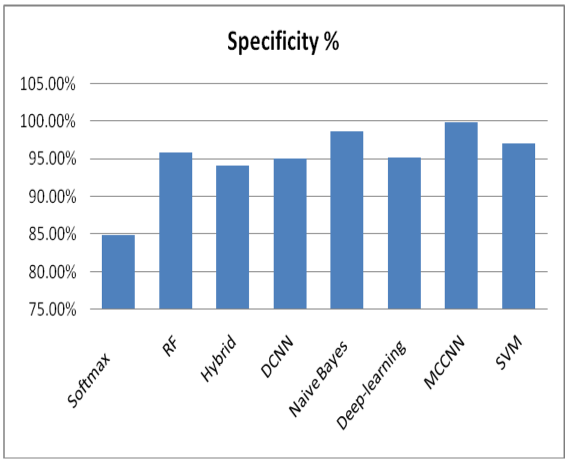


Fig. 5. Comparative Analysis of specificity of Classifiers

With the help of these three parameters analysis of thyroid nodule classification has been done. Performance by CNN methodologies gives good results. Research can takes advantages of limitation of each model explained above to develop a new model which would gives a higher performance for thyroid nodule classification.

IV. CONCLUSION

Ultrasound imaging is one of the popular techniques for thyroid nodule classification and identification of thyroid disorder. Experienced radiologist can do proper diagnosis of thyroid lesions. As there is growing thyroid disease overall in the world, there is burden on radiologist for accurate detection of thyroid nodules in benign or malignant appearance. To reduce dependency factor many CAD systems have been designed. But now a day's CNN based CAD system using the deep learning approach is used which gives accurate, fast, objective classification of thyroid nodules. This paper reviews the latest CAD systems for identification of thyroid nodules and compares results of different deep learning algorithm. In the forthcoming days, analysis of a different computerized automated system with deep learning methods for new disease shall be explored.

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