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Survey on Thyroid Nodule Classification Techniques

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Abstract - According official statistics, cancer is the second leading cause of human fatalities. Among various types of cancer, thyroid cancer is currently prevailing. Treatment of thyroid nodules involves proper identification of the type. Human centered diagnosis is usually error prone, resulting in the interest towards automating the process. In this paper, various techniques for thyroid nodule detection and classification based on MRI are discussed. Various feature extraction strategies like LSDA, Relief-F, HOG, SIFT and so on are studied in association with classifiers like SVM, kNN, MLP, decision tree and others. The performance of pretrained CNNs like AlexNet, GoogLeNet and ResNet for feature extraction and classification are also considered for study.

Key Words: Thyroid Nodule, USG, Biopsy, Neural Networks, Feature Extraction

1. INTRODUCTION

The thyroid gland is an endocrine gland in the neck consisting of two connected lobes. The lower two thirds of the lobes are connected by a thin band of tissue called the thyroid isthmus. The thyroid gland secretes three hormones: the two thyroid hormones – triiodothyronine (T3), and thyroxine (T4), and a peptide hormone, calcitonin. The thyroid hormones influence the metabolic rate and protein synthesis, and in children, growth and development. Calcitonin plays a role in calcium homeostasis. Secretion of the two thyroid hormones is regulated by thyroid-stimulating hormone (TSH), which is secreted from the anterior pituitary gland. Thyroid disorders include hyperthyroidism, hypothyroidism, thyroid inflammation (thyroiditis), thyroid enlargement (goiter), thyroid nodules, and thyroid cancer.

Thyroid nodules are often found on the gland. The majority of nodules do not cause any symptoms, thyroid hormone secretion is normal, and they are non-cancerous. Non-cancerous cases include simple cysts, colloid nodules, and thyroid adenomas. Malignant nodules, which only occur in about 5% of nodules, include follicular, papillary, medullary carcinomas and metastases from other sites. Benign nodules need only monitoring mostly but malignant ones might need surgery, radiation and chemotherapy. Determining the type of nodules involves physical examination, blood tests, ultrasound imaging, biopsy and genetic testing.

Small cancers usually don't need any treatment as the risk of spreading is very less. In such cases doctors advise constant monitoring. Other situations require treatments like surgery, radiation and chemotherapy. This indicates the paramount importance of determining the type to tumor in patient survival. Invasive biopsies are ordered to be sure of the diagnosis. Both scans and biopsies are prone to human error. To avoid errors in diagnosis and increase accuracy automated systems are being developed. In recent years there has been a lot of research in this regard using various machine learning techniques. Before the advent of deep learning, feature selection techniques like LSDA, Relief-F, HOG, SIFT and so on followed by classifiers like SVM, KNN, MLP and others are used. Now the primary focus is on utilizing neural networks to achieve more promising results.

2 LITERATURE REVIEW

[1] propose a novel automated thyroid nodule detection and classification system. Raw images of thyroid nodules recorded using high resolution ultrasound (HRUS) are subjected to Gabor transform. The extracted features are reduced by Locality Sensitive Discriminant Analysis (LSDA) and ranked by Relief-F method. Over-sampling strategies like SMOTE with Wilcoxon signed-rank, Friedmans and Iman-Davenport post hoc tests are used to balance the classification data and to improve the classification performance. Classifiers such as Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Multi-Layered Perceptron (MLP) and Decision Tree are used for the characterization of benign and malignant thyroid nodules. C4.5 achieved the highest classification accuracy of 94.3% among other techniques.

[2] use a deep learning approach to extract features from thyroid ultrasound images. Ultrasound images are pre-processed to calibrate their scale and remove the artifacts. A pre-trained GoogLeNet model is then fine-tuned using the pre-processed image samples which leads to superior feature extraction. The extracted features of the thyroid ultrasound images are sent to a Cost-sensitive Random Forest classifier to classify the images into malignant and benign cases. The proposed model achieves accuracy of 99.13% for the 693 images considered.

[3] adopt a VGG-F model trained with ImageNet data to the ultrasound image domain, to generate semantic deep features under small sample condition. Then, those deep features are combined with conventional features such as

Histogram of Oriented Gradient (HOG) and Scale Invariant Feature Transform (SIFT) together to form a hybrid feature space. Furthermore, to make the general deep features more pertinent to the problem, a feature subset selection process is employed for the hybrid nodule classification. The classification is performed using the RBF kernel SVM classifier. Accuracy of the system is 92.9%.

[4] propose a hybrid method for thyroid nodule diagnosis, which is a fusion of two pre-trained convolutional neural networks (CNNs) with different convolutional layers and fully-connected layers. Firstly, the two networks pre-trained with ImageNet database are separately trained. Secondly, feature maps learned by trained convolutional filters, pooling and normalization operations of the two CNNs are fused. Finally, with the fused feature maps, a softmax classifier is used to diagnose thyroid nodules. Accuracy of 83.02% is obtained upon using fused CNNs.

[5] evaluate the diagnostic value of combination of artificial neural networks (ANN) and support vector machine (SVM)-based CAD systems in differentiating malignant from benign thyroid nodes with gray-scale ultrasound images. Two morphological and 65 texture features extracted from regions of interest in 610 2D-ultrasound thyroid node images were used to develop the ANN and SVM models. ANN was used to find better parameters for training SVM. This combination results in 92% accuracy.

[6] apply the method of transfer learning to classify the malignant and benign thyroid nodules based on their ultrasound images. The principal steps are preprocessing, data augmentation and classification by transfer learning. The preprocessing concentrates in extracting the region of interest (ROI). After the augmentation of dataset using traditional methods and CNN, a pre-trained Residual Network is adopted to do transfer learning, and the parameters of this pre-trained net are fine-tuned with three different datasets attained including the original dataset, the augmented dataset via traditional methods and the augmented dataset via convolutional network. The resulting classification accuracy is 93.75%.

[7] explore the potential of Extreme Learning Machine (ELM) to discriminate benign and malignant nodules. The features subsets are identified using the ReliefF feature selection method, and then the obtained feature subsets are evaluated one-by-one on the test set via a cross validation scheme based on ELM classification. Finally, the features in the subset with the best classification accuracy are considered as the most discriminative features. The best accuracy obtained was 87.72%.

[8] propose an automatic method applied to the thyroid ultrasound images for lesion localization and diagnosis of benign and malignant lesions. The FCN-AlexNet was used to segment images, and accurate localization of thyroid nodules was achieved. Then, the method of transfer learning was introduced to solve the problem of training data shortages during training process. After AlexNet is used to classify the localization area. Accuracy of 90.7% is obtained from this system.

[9] propose a novel Sal-deep network model to achieve the classification and diagnosis of thyroid cancer, which can simulate visual attention mechanism. The Sal-deep network introduces saliency map as an additional information on the deep residual network, which selectively enhances the feature extracted from different regions according to the mask map. Sal-deep model has two inputs: raw feature maps before selective enhancement and saliency masks as selective enhancement basis. The output enhances feature maps after selective enhancement. 86.69% accuracy is obtained from the proposed system.

[10] aim to design a CAD system which uses only direction independent features. The 60 thyroid nodules (20 malignant, 40 benign) are divided into small patches of 17 × 17 pixels, which are then used to extract several direction independent features by employing Two-Threshold Binary Decomposition (TTBD), a method that decomposes an image into the set of binary images. The features are then used in Random Forests (RF) and Support Vector Machine (SVM) classifiers to categorize nodules into malignant and benign classes. RF obtains 95% accuracy while SVM attains 91.6% accuracy.

[11] attempt to develop a CAD system that analyzes internal and external characteristics of nodules more objectively. Three steps involved are, firstly, a pre-processing step was applied to remove label and reduce speckle noise by applying Adaptive Median Filter followed by Bilateral Filter. Secondly, Active Contour and Morphology operation were applied to segment the nodules. Subsequently, geometric and texture features were extracted. In the final step, Multi-Layer Perceptron was used to classify internal characteristics while Support Vector Machine was used for classifying external characteristics. Accuracies of 97.78% and 94.44% are obtained for external and internal characteristics respectively.

[12] propose a novel deep-learning-based CAD system, guided by task-specific prior knowledge, for automated nodule detection and classification in ultrasound images. The system consists of two stages. First, a multi-scale region-based detection network is designed to learn pyramidal features for detecting nodules at different feature scales. The region proposals are constrained by the prior knowledge about size and shape distributions of real nodules. Then, a multi-branch classification network is proposed to integrate multi-view diagnosis-oriented features, in which each network branch captures and enhances one specific group of characteristics that were generally used by radiologists. ResNet and ZFNet are chosen as the backbone of detection and classification networks respectively. The system achieves a diagnostic accuracy of 97.1%.

Table -1: Related works comparison

Sl. No.	Authors	Techniques	Accuracy
1	U Rajendra Acharya, Pradeep Chowriappa, Hamido Fujita, Shreya Bhat, Sumeet Dua, Joel E.W. Koh, L.W.J. Eugene, Pailin Kongmebhol, K.H. Ng	Gabor Transform, LSDA, Relief-F, SMOTE, kNN, SVM, MLP, C4.5	94.3% (C4.5)
2	Jianning Chi, EktaWalia, Paul Babyn, Jimmy Wang, Gary Groot, Mark Eramian	GoogLeNet, Random Forest	99.13%
3	Tianjiao Liu, Shuaining Xie, Yukang Zhang, Jing Yu, Lijuan Niu, Weidong Sun	HOG, SIFT, VGG-F, RBF kernel SVM	92.9%
4	Jinlian Ma, Fa Wu, Jiang Zhu, Dong Xu, Dexing Kong	CNN	83.02%
5	Qin Yu, Tao Jiang, Aiyun Zhou, Lili Zhang, Cheng Zhang, Pan Xu	ANN, SVM	92%
6	Ye Zhu, Zhuang Fu, Jian Fei	CNN, ResNet	93.75%
7	Jianfu Xia, Huiling Chen, Qiang Li, Minda Zhou, Limin Chen, Zhennao Cai, Yang Fang, Hong Zhou	Relief-F, ELM	87.72%
8	Jianguo Sun, Tianxu Sun, Ye Yuan, Xingjian Zhang, Yiqi Shi, Yun Lin	FCN-AlexNet	90.7%
9	Yanming Zhang	Sal-deep model	86.69%
10	Antonin Prochazka, Sumeet Gulati, Stepan Holinka, Daniel Smutek	TTBD, RF, SVM	95%(RF) 91.6%(SVM)
11	Hanung Adi Nugroho, Zulfanahri, Eka Legya Frannita, Igi Ardiyanto, Lina Choridah	Adaptive Median Filter, Bilateral Filter, Active contour, ELM, SVM	97.78% (external characteristics) 94.44% (internal characteristics)
12	Tianjiao Liu, Qianqian Guo, Chunfeng Lian, Xuhua Ren, Shujun Liang, Jing Yu, Lijuan Niu, Weidong Sun, Dinggang Shen	ResNet, ZFNet, GGVF-Snake, Fast-RCNN	97.1%

3. CONCLUSION

Owing to the increase in thyroid cancer cases, lot of research has been carried to automate its detection and classification. With the advancement in machine learning, neural networks have become the primary focus of interest in developing models for thyroid nodule diagnosis. Transfer learning techniques can be applied to these models and hence used for other similar diagnosis. This paper attempts to summarize few techniques designed for thyroid nodule classification. There is still a need for further research an enhancement of techniques in this regard to ensure that the developed systems can be deployed for use by doctors.

REFERENCES

[1] U Rajendra Acharya, Pradeep Chowriappa, Hamido Fujita, Shreya Bhat, Sumeet Dua, Joel E.W. Koh, L.W.J. Eugene, Pailin Kongmebhol, K.H. Ng, “Thyroid lesion classification in 242 patient population using Gabor transform features from high resolution ultrasound images”, Elsevier, Knowledge-Based Systems, Volume 2213, pages 1-11, 2016.

[2] Jianning Chi, EktaWalia, Paul Babyn, Jimmy Wang, Gary Groot, Mark Eramian, “Thyroid nodule classification in ultrasound images by fine-tuning Deep Convolutional Neural Network”, Springer, Journal of Digital Imaging, Volume 30, Issue 4, pages 477-486, 2017.

[3] Tianjiao Liu, Shuaining Xie, Yukang Zhang, Jing Yu, Lijuan Niu, Weidong Sun, “Feature selection and thyroid nodule classification using Transfer Learning”, IEEE 14th International Symposium on Biomedical Imaging, pages 1096-1099, 2017.

[4] Jinlian Ma, Fa Wu, Jiang Zhu, Dong Xu, Dexing Kong, “A pre-trained Convolutional Neural Network based method for thyroid nodule diagnosis”, Elsevier, Ultrasonics, Volume 73, pages 221–230, 2017.

[5] Qin Yu, Tao Jiang, Aiyun Zhou, Lili Zhang, Cheng Zhang, Pan Xu, “Computer-aided diagnosis of malignant or benign thyroid nodes based on ultrasound images”, Springer, European Archives of Oto-Rhino-Laryngology, Volume 274, Issue 7, pages 2891–2897, 2017.

[6] Ye Zhu, Zhuang Fu, Jian Fei, "An Image Augmentation method using Convolutional Network for thyroid nodule classification by transfer learning", IEEE, 3rd International Conference on Computer and Communications (ICCC), pages 1819-1823, 2017.

[7] Jianfu Xia, Huiling Chen, Qiang Li, Minda Zhou, Limin Chen, Zhennao Cai, Yang Fang, Hong Zhou, "Ultrasound-based differentiation of malignant and benign thyroid Nodules: An Extreme Learning Machine approach", Elsevier, Computer Methods and Programs in Biomedicine, Volume 147, pages 37-49, 2017.

[8] Jianguo Sun, Tianxu Sun, Ye Yuan, Xingjian Zhang, Yiqi Shi, Yun Lin, "Automatic diagnosis of thyroid ultrasound image based on FCN-AlexNet and Transfer Learning", IEEE, 23rd International Conference on Digital Signal Processing (DSP), pages 1-5, 2018.

[9] Yanming Zhang, "Classification and diagnosis of thyroid carcinoma using Reinforcement Residual Network with Visual Attention Mechanisms in ultrasound images", Springer, Journal of Medical Systems, pages 43-323, 2019.

[10] Antonin Prochazka, Sumeet Gulati, Stepan Holinka, Daniel Smutek, "Patch-based classification of thyroid nodules in ultrasound images using Direction Independent Features extracted by Two-threshold Binary Decomposition", Elsevier, Computerized Medical Imaging and Graphics, Volume 71, pages 9-18, 2019.

[11] Hanung Adi Nugroho, Zulfanahri, Eka Legya Frannita, Igi Ardiyanto, Lina Choridah, "Computer aided diagnosis for thyroid cancer system based on internal and external characteristics", Elsevier, Journal of King Saud University – Computer and Information Sciences, 2019.

[12] Tianjiao Liu, Qianqian Guo, Chunfeng Lian, Xuhua Ren, Shujun Liang, Jing Yu, Lijuan Niu, Weidong Sun, Dinggang Shen, "Automated detection and classification of thyroid nodules in ultrasound images using clinical-knowledge-guided Convolutional Neural Networks", Elsevier, Medical Image Analysis, Volume 58, 2019.