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Anomalies in Thyroid Gland Images Based on Feature Extraction From Capsule Network Architecture

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Abstract

Diagnosing benign and malignant glands in thyroid ultrasound images is considered as a challenging issue. Recently, deep learning techniques have significantly resulted in extracting features from medical images and classifying them. Convolutional networks ignore the hierarchical structure of entities within images and do not pay attention to spatial information as well as the need for a large number of training samples. Capsule networks consist of different hierarchical capsules equivalent to the same layers in the CNN neural network. This study tried to extract textural features using a deep learning model based on a capsule network. Thyroid ultrasound images were given to the capsule network as input data, and finally the features learned in the capsule network were used to teach the Support Vector Machine classifier, in order to diagnose thyroid cancer. Experimental results showed that the proposed method with 98% accuracy has achieved better results compared to convolutional networks.

Keywords: *Thyroid Gland, Convolutional Neural Network (CNN), Deep Learning, Feature Extract, Capsule Network*

1. Introduction

The thyroid gland is located in the human neck and the body's metabolism is preserved by this gland. Thyroid diseases can be summarized in the following two fields: 1- hypothyroidism and hyperthyroidism, and 2- Thyroid cancer. In the field of thyroid cancer, which is a tumor developing in the thyroid gland of the body, it is considered as an abnormality. Medical images of this gland helps doctors in better diagnosing benign or malignant. Among radiographic images of body structure, ultrasound is known as a valuable diagnostic method for the thyroid.

With the increased prevalence of deep learning methods in some applications such as images classification, object diagnosis, and feature extraction from images, a major step has been taken into account in the field of medical images. The researchers mostly try to use different neural network techniques, in order to identify cancer cells, and in the meantime, they realized the great potential of CNN networks as a powerful tool in automatic diagnosis of image patterns. Notably, feature extraction from images based on neural network is considered as one of the applications of deep learning. Among the neural networks used, pre-trained networks play a significant role, as in 2017 from the Google-Net pre-trained network, these have been used for feature extraction and anomaly diagnosis in the thyroid gland [1]. Correspondingly, various pre-trained networks have been used in similar works [2-7]. In 2018, the efficiency of using artificial neural networks in diagnosing thyroid abnormalities has been compared to the work of radiologists, and a large difference has been observed in their accuracies [8]. In 2019, the diagnosis and classification of abnormalities in thyroid gland ultrasound images were performed based on the Res-Net pre-trained network [9]. In another study, better efficiency of these networks in diagnosis was mentioned using several pre-trained models and comparing transmission learning in these models [10]. In other studies, large-scale data have

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been studied using the Inception-v3 pre-trained network [11].

However, in CNN networks, because the pooling function leads a number of image features to be lost, a large amount of data is needed to train the network. Of course, the most important weakness of CNN is its inability in diagnosing the position of the image and changing the shape and texture of the image. Moreover, they cannot handle the images from different angles and eventually a lot of information will be lost. In 2016, to compensate for the CNN network defects, the capsule network was provided by sara sabure [12]. The capsule network, which its architecture is different from other neural networks, in the encoder section, can easily encrypt the specifications and spatial connections of the features in the images. Capsule networks use a group of neurons as a capsule, so that all the important features in the capsule are preserved in form of a vector. CapsNet with a dynamic routing mechanism mostly use the similarity of different hierarchical capsules (equivalent to layers in CNN networks) to update the weight, and this feature causes extracting more information from the images. As a result, better feature vectors would be extracted. In a study, the effect of capsule networks in confronting with the challenges of medical images, was considered [13].

In this study, a deep learning method based on the capsule network was introduced in order to extract useful features from thyroid gland ultrasound images. In addition, the capsule network was used as a feature extractor to obtain important features of the gland and following reducing the features, SVM classifier was used as an anomaly detector. According to a recent study, PCA method is known as the best feature selection method and SVM is known as the best classifier method; therefore, these two methods were used in this study [14]. The proposed model was found to be able to achieve a better diagnosis compared to the conducted works with 98% accuracy.

The main contribution of this study can be summarized in the following two aspects: 1- a capsule network was designed in order to remove the challenges of using CNN network in extracting features from images, so the final feature vector was obtained by adjusting the network parameters in the layers of its encoder section, and finding useful features consequently led to better diagnosis; and 2- The SPCA method was used in order to reduce the obtained features and the SVM classifier was also used to diagnose the anomaly. In fact, the superiority of the proposed model is in using the capsule network to learn the features and the SVM classifier both to diagnose the anomaly and to use the benefits of deep learning and machine learning in combination.

The remained the article were organized as follows: Section 2 presents the previous related work, Section 3 expresses a brief definition of feature extraction and its advantages and disadvantages in CNN and CapsNet networks, section 4 describes the proposed method, section 5 discusses the experimental results; and Section 6 reports the results.

2. Related Works

Diagnosis of thyroid-related diseases is known as one of the most important research areas related to the classification issues in data mining and machine learning science [15]. In a study, the support vector machine model was used to diagnose hypothyroidism or hyperthyroidism [16]. In [17], with the aim of comparing the effect of several different data mining models on several different types of disease. The models used were decision tree, neural networks, logistic regression, support vector machine, and Naïve Bayes. Additionally, the diseases investigated were diabetes, breast cancer, and hyperthyroidism. Research results has shown that the support vector machine works better compared to the others.

In another study, a dissimilar approach was done to solve the problem of thyroid diagnosis. This study aimed to analyze the data of crotch and tongue medical images in order to diagnose either hyperthyroidism or hypothyroidism. Accordingly, the use of several separate indicators to extract features is one of the innovations of this research [18]. In [19], using the MS-Apriori method, positive and negative rules were created in relation to the features used in the database. The function of this method is to map the features to a better answer space for fitting the model as well as ranking the initial features. After ranking the features, the important features remained and the weak features were eliminated. Finally, thyroid disease was predicted using the reference machine learning models and the accuracy of the models were compared with each other. A new study diagnosed thyroid cancer based on analyzing the internal and external characteristics in thyroid ultrasound images [20]. Moreover, another article diagnosed breast cancer based on the feature extraction using supervised and unsupervised algorithms, while examining various methods of feature reduction [21].

The use of deep neural networks is one of the positive strategies in the extraction and classification of textural features. In another article, thyroid gland images were collected by cytopathology, which were then used to develop a deep learning model for diagnosing thyroid bulges (nodules) and disorders. It was found that the use of image features that are specific to thyroid deficiencies greatly enhances the performance of the model. The diagnostic accuracy of this model is 87%, which is higher compared to those of the reference learning machine models [22]. In another research, ultrasound data analysis, which is performed based on ultrasonic waves, was used to diagnose thyroid deficiencies. Of note, the algorithm used was the CNN method, and the accuracy of the diagnostic model was 95%. Regarding the claim of this article that there are great improvements in the extraction of thyroid-specific features in images of thyroid deficiency, improving the methods of extracting local features from the images turned to be the main goal in the proposed model of this study [23]. The effect of deep learning on the management of the thyroid glands in ultrasound images was also discussed in detail in the article [24]. Additionally, a comprehensive review of the capsule network architecture and its use in different fields were discussed and then compared to CNN networks in the article [25].

Recently, the capsule neural network was used to classify tumors. In [26-28], the capsule network was used to diagnose and classify different types of cancers. In [29], Alzheimer's disease was diagnosed using the capsule network. In [30], the capsule network was also used to diagnose iris problems. In the study by [31], the combination of capsule network and convolutional was used in the non-medical field that is worth pondering. Several reviews on thyroid cancer have provided a better perspective into the progress of this research [32-34]. In the work by [35], the improvement of Principal Component Analysis method was considered as SPCA, which was then used in selecting effective features.

3. Comparison of Capsule and CNN Networks

Feature extraction refers to the process of converting the raw pixels of an image into useful and meaningful information. These features can be extracted both manually and automatically by neural networks. During this process, the low level features in the images such as color, texture, and shape are firstly identified and then the high level features are discovered by low level features. Thereafter, the features extracted from the images are shown in numerical values. The feature extraction operation in convolutional networks is mostly done in two parts as follows: convolutional layers and pooling layers. Thus, using convolutional layers, the filter is multiplied in the local area of the input, and with this operation, feature maps is automatically obtained in several steps. In fact, in the obtained feature maps, the main elements are identified among the pixels of the image. In the next step, using the pooling layers, the dimensions of the extracted feature maps are reduced in several steps. Disadvantages of convolutional networks are the large number of training parameters, the need for a lot of training data, and their time–consuming feature. In fact, the pooling function in CNN leads a number of image features to be lost, and a lot of training data are then needed to compensate for this problem. In recent years, to solve the problem of lack of training data, pre-trained CNN networks such as Resnet, vgg-net, and google-net were used instead of CNN network, so that transfer learning is used in these networks. In fact, by transferring the weights of the trained network (on the big data set) to the new model, the pre-trained model can be re-used for another time on different data sets. Accordingly, this work had a very good result for the diagnosis of thyroid gland anomalies in recent years.

Capsules established a new basis in artificial intelligence that helps deep learning to model hierarchical relationships better within neural networks. Capsule networks include hierarchical capsules that have actually replaced layers in CNN neural networks. As well, low-level capsules include a large number of capsules that are small in size.

However, in high-level capsules, the dimensions increased, and the number of capsules decreased. This may be due to the location information that are stored in capsule dimensions. In addition, the number of low-level capsules is large, so each capsule represents only a small area of inputs, but as the capsule level increases, a larger area is indicated by each capsule, while the number of capsules is decreasing. Therefore, during the transfer of a low-level capsule to a high-level capsule, there is an increase in dimensions.

High-level capsules are weighed from the sum of low-level capsules, and due to the similarity of hierarchical capsules, the weights are finally updated. Each dimension of the capsule is considered as a feature (texture, color, etc.) and all important information on the status of the feature that we are trying to identify, are summarized and then accumulated in form of a vector. As can be observed, the scalar output of the feature screen on CNN was replaced by the vector output on the capsule network. On the other hand, because CNNs cannot handle images from different angles, the capsule network usually uses a dynamic routing mechanism, and by this mechanism, the ability to understand three-dimensional space is defined, which ultimately provides more desirable and meaningful features. In general, CNNs have a longer training time than CapsNet, because their depth is great and also because they are deep in width, so require fewer parameters. Regarding all the above-mentioned cases, a research has shown that capsule networks could reduce error of objects diagnosis in images by 45%. Therefore, in this study, the capsule network was used to extract the feature.

The capsule network has two parts in terms of architecture as follows: encoder and decoder. Accordingly, the encoder part consists of the following 3 layers: 1- convolutional layer, 2- Primary capsule layer, and 3- Digit-caps layer. Moreover, the decoder part is equivalent to fc layers in CNN network. In the first layer of the encoder, a traditional convolutional layer with a Relu activity function is used to extract the primary feature maps. The second layer, or primary capsule, takes the primary features from the first layer and then divides them among the capsules. Thereafter, each capsule is multiplied by a weight matrix and the output of the layer is also determined. In the third layer, or digit caps, dynamic routing operation is used for the capsules, and the feature vector is taken as the output from this layer. The decoder part, which is used for classification, is similar to the FC layers on CNN.

According to the mentioned descriptions, capsule neural network is able to be more successful than CNN in the field of feature extraction by considering the spatial connections of features in the image.

4. Suggested Method

The proposed method includes the following main parts. (Fig.1)

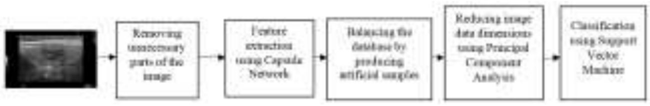

Fig. 1.Steps to diagnose anomalies in the proposed method

4.1. Pre-Processing

Preliminary images include transcripts that contain information about patients and their condition by imaging systems. This section was deleted using the cropping method. In this method, the image border size is initially obtained using its main borders, and segmentation is done before final deletion. The centroid points of the image objects are calculated and then the area of each part is returned in segmentation (each object is considered an island-shaped area of pixels with high brightness). Next, the areas with more area are considered as the main part of the image and the rest as the background. This can greatly reduce the sensitivity of images to noise. (Fig.2)

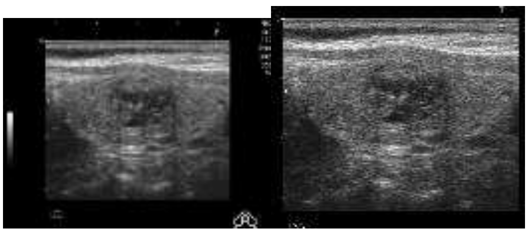

Fig. 2. The initial input (right) and output (left) images after preprocessing

4.2. Extracting Features Based on Deep Learning

In this phase, the spatial features of each image are extracted using the capsule network. In capsule networks, global features are restored using a color intensity gradient, in addition to extracting local features.

Since the purpose of using the capsule network is only to extract the desired features from the images, the decoder part, which is used for both image reconstruction and classification, was omitted in this study, and only the encoder part of the capsule network remained to be designed.

CapsNets are a special type of CNNs that adapt local features by changing their structure and creating a layer, called a capsule, consisting of hundreds of neurons. Three general layers are used in the CapsNet. There is a classic CNN in the first layer. This layer extracts local features (low-pass level) according to the color intensity of the pixels and provides them to the capsule layer. The convolution layer has 256 channels and 9 × 9 size kernels with stride 1 (the activation function of this layer is RELU). The second layer consists of the CapsNet, which is referred to as the primary capsules. There are 32 channels in the second layer, each of which includes eight primary capsules with a convolution layer with a length of 256 channels and 9 × 9 kernels. Therefore, the output vector of each capsule (w) is 256 × 81 long, which can extract local properties with high accuracy. Generally, the primary capsules in the second layer will have an output of 32 × 56 × 56 long (each capsule consists of eight dimensions) according to the input image size. In the final layer, there are numerical capsules (calculators) that produce the final properties from the capsule layer (this layer indicates the possible presence of a sample from each class). Given that the capsule layer contains 32 channels with a size of 56 × 56, and since 10 capsules are considered in the third layer, the size of this layer is 56 × 56 × 32 × 10. Fig. 3 shows the general structure of the CapsNet.

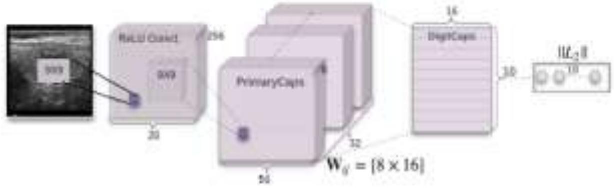

Fig. 3. Schematic of the CapsNet

It should be noted that only feature extraction is performed in the capsule network used by the researcher. Therefore, it is critical to use a dynamic routing algorithm between the second and third layer capsules (because the output of the first layer is one-dimensional, routing does not take place between this layer and the primary capsule layer). Here, the output of each capsule (u) is sent to the third layer capsules (v0-v9) with the same probability vector (at the beginning, there is the same probability of receiving u vector, i.e. local properties, by the numerical capsules). In other words, the i^{th} capsule in the L-layer tries to detect the output of the j^{th} capsule in the L+1 layer. Over several consecutive rounds, the output of capsule j (vj) is finally sent to capsule i by a nonlinear function called squash (Equation 1). Here, s_j is the length of the vector received by the numerical layer (calculator). Finally, the output of V_j for each calculator capsule will be the vector of the properties extracted by the CapsNet (10 capsules each extracting 16 features according to the length of vector w).

$$V_j = \frac{||S_j||^2}{1 + ||S_j||^2} \times \frac{S_j}{||S_j||} \qquad (1)$$

4.3. Balancing in the Features set

The thyroid cancer sample label has two general classes where the number of positive samples (with cancer) is minor compared to negative samples. This can cause an imbalance of the data set and directly affect the classification process of learning models. For this reason, this section uses the synthetic minority oversampling technique (SMOTE) algorithm, in which synthetic samples are generated from real data (textural feature vector in the minority class) and added to the model. The different steps of the SMOTE algorithm are as follows [36]:

1. Isolation of minority classes, including positively labeled specimens (with thyroid cancer).
2. For all minority samples (x), a sample (y) is randomly selected from the neighboring k (in this article k is equal to 5) directly to calculate the difference between x and y.
3. Generation of a new sample by multiplying a normal random number by the output obtained from the second step and adding it to the original sample or x.

By generating new samples, a balance is established in the textural feature set and conditions are provided for the selection of effective feature vectors.

4.4. Reducing the Dimensions of Textural Features using the Principal Component Analysis (PCA)

After extracting the features that could be obtained from the image, a suitable number of them were selected in order to perform the classification operation. Among these obtained features, there were some additional and irrelevant features definitely. So, it was hypothesized that by removing them at this stage, the number features would be reduced, training time would be decreased, and as a result the efficiency of SVM classifier would be improved. In this research, using the SPCA method based on the research by [35], a set with low-dimension features was extracted from a set with high-dimension features. The SPCA method is a type of PCA that tries to describe each principal component (PC) as a linear combination from a subset of real variables, making it easier to understand the model. However, in PCA, each principal component is a linear combination from all real components, which makes it difficult to interpret the model.

Considering the basic logic of the PCA, each numerical matrix can be represented as a linear combination of part of its input values in the form of new variables. These variables describe the main properties of the matrix and remove the content overlap from the data due to their orthogonal nature (37-39). In the first step, a variable (e.g. P1) is sought to be able to establish the condition of Equation 2 in a matrix of size $X_{n \times k}$.

$$P_1 = X_{t1} \qquad , \left|\left|t1\right|\right| = 1 \tag{2}$$

In statistics, the higher the variance at one point, the higher the accumulation of information in that area. Therefore, Equation 3 can be expressed as maximizing the variance of variable P1 (matrix V) (40).

$$Var(P1) = \frac{1}{n}\ ||P1||^2 = \frac{1}{n}\ t'X'Xt1 = t_1'\ , \qquad Vt1V = \frac{1}{n}\ X'X \tag{3}$$

Equation 3 can be maximized using the Lagrangian coefficient.

$$L = t_1'Vt1 - \lambda(t_1't_1 - 1) \tag{4}$$

By calculating the partial derivative of L relative to t1 and λ1, t1 is the normalized vector V and λ1 is its corresponding value.

$$\begin{cases} \dfrac{\partial L}{\partial t_1} = 2vt_1 - 2\lambda_1 t_1 = 0 \\ \dfrac{\partial L}{\partial \lambda_1} = -(t_1' - t_1) = 0 \end{cases} \qquad Vt_1 = \lambda_1 t_1 \tag{5}$$

After the steps mentioned above, the unknown value of t1 is the normalized vector corresponding to the maximum value of λ1 or the principal diameter (eigenvector) of matrix V. The structural variable $P_1 = X_{t1}$ is the principal component of the first entry in the V matrix (hence, m principal component of V can be obtained using $P_m = X_{tm}$). The final output of the PCA algorithm (matrix V) is the same size as the input matrix and each input refers to a specific score or value. In the last step, the sum of the information in P is returned by Equation 6 to reduce the data dimensions and select the effective properties of matrix V to reach the threshold value, t_h, as the final properties (here, t_h value is considered 0.9).

$$final_{indexes} = \sum_{i=1}^{m} Var(Pi) \leq th \tag{6}$$

4.5. Diagnosis of Anomalies by SVM Classifier

In the last step of the proposed method, the principal components extracted from the properties matrix are assigned to the SVM classifier. SVM provide good generalisation when the parameters are appropriately configured, even if the training set has some bias. SVM deliver a unique solution, since the loss function is convex; and in principal it can model any training set, when an appropriate kernel is chosen. In this model, the choice of the location of the hyperplanes in the problem space and the maximization of the margins between them are directly related to the distribution style of samples. In general, the SVM has three main linear, polynomial, and Radial Basis Function kernels, each of which can select the location of the hyperplanes in the problem space with high accuracy. The basic challenge of SVM is low accuracy in dealing with low-repetition input samples. This feature has largely been eliminated using the K-Fold Cross Validation method. Here, the input dataset is assigned to the model in k steps and each time $\frac{1}{k}$ of data is considered as a test (main diameter of the data). In the current study, parameter k is set to 5.

4.6. Experimental Results

The dataset used in this study were thyroid ultrasound images data provided by the Society of Photo-Optical Instrumentation Engineers. Accordingly, this dataset contains 480 thyroid ultrasound images belonging to 298 individuals. Each sample includes an ultrasound image and a description file. In this research, all the tests were performed on Intel (R) Core (TM) i5-2430M system with 2.40GHz CPU, 12.0GB RAM, and using Windows 10. Thereafter, the algorithm was run on Python 3.8. After cropping the 360 * 360 image, the image size decreased to 28 * 28 and was then given to the capsule network as input, and after extracting the effective features and when diagnosing and using SVM, the *5-Fold Cross Validation* tool was used to manage the data training. Finally, the average result of these 5 validations was chosen as the ultimate estimate. Success evaluation parameters of feature extraction method are model accuracy, sensitivity, specificity, given in equations 7 to 9.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \tag{7}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100 \tag{8}$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{9}$$

The tests' results showed that the proposed method has a better performance (Table 1).

Table 1
Comparison of the diagnostic parameters of the proposed model (CAPSNET) with those of previous models (CNN).

Specificity%	Sensitivity%	Accuracy%	Method for Feature Extraction	Reference
97.96	92.77	94.70	CNN	Qin et al. [10]
87.20	88.2	87.80	CNN	Shi et al. [5]
99.30	82.80	96.34	CNN	Chi et al. [1]
64.17	80.69	97.33	CNN	Moussa et al. [9]
82.10	91.20	88.15	CNN	Ko et al. [8]
97.22	96.64	98.20	CAPSNET	Proposed model

5. Discussion

The reason for this result improvement may be the technical performance of these two networks. In the CNN network, by performing the pooling operation, the image features are learned regardless of their position, or in other words, the spatial relationships between the features are ignored. For example, the parts of a machine in the image are known alone, but they are not necessarily recognized as these parts belong to the machine, because their position is not known by pooling unfortunately. Therefore, it is not learned whether each one of these parts is on the right or left side of the image or whether the shape has rotation, so it can be said that they do not have equivalence. The presence of this feature in the capsule network as a distinction point with CNN, leads to learning more information from the images. In fact, CapsNets not only teach good weights for image extraction and classification, but also they can help in understanding the positional parameters of the image well (spatial changes like rotation). Basically, in the capsule network, only in the first layer, the convolution operation is performed and the primary features (such as the edges of the image) are extracted. As well, instead of the pooling operation, the primary features are divided among the capsules in the second layer. Correspondingly, each capsule is a vector multiplied by the weight matrix and hierarchically lower-level capsules send their input to higher-level capsules that are better matched with their input. Thereafter, the weight is updated during this operation, and this mechanism is so-called "dynamic routing" in the capsule network. Despite this mechanism, the capsule network finds and learns the spatial connections among features (pooling would lead to the loss of the spatial connections between features). Therefore, all the important features learned by the capsule network in form of a vector (capsule) were maintained and for the above-mentioned reasons, the accuracy of features' diagnosis was much higher than CNN, which led to strengthen the model. In this study, 480 ultrasound images were used, which were given to capsule network after the preprocessing phase, in order to learn the proper features. Feature extraction by pre-trained networks has received much attention in previous studies. Of course, in pre-trained networks, we faced the challenge of resetting the network on its data, so the diagnosis accuracy would vary by changing the network setup parameters. Additionally, sometimes with a large number of training parameters, optimal accuracy can be achieved. On the other hand, convolutional networks are less efficient on complex images and the use of pre-trained networks does not help in solving this problem. In fact, setting up a pre-trained network is just faster and easier than training a CNN network, and this is the reason that they are being replaced by a CNN network. Regarding the above-mentioned cases, CapsNets seem to be a new promising technique for both diagnosing and classification. The experimental results of using the capsule neural network in the studies indicated that with different architectures that have been shown compared to other neural networks, it has the ability of encrypting the spatial connections of the image features. So, it is more effective on image diagnosis, and in this study, this effect was clearly visible.

6. Conclusion and Recommendations

Deep learning in the field of medical images has occupied the heavy burden of feature extraction. CNN neural networks play a significant role in this area. Because CNNs cannot evaluate images from different angles, capsule networks have been introduced. Accordingly, it was shown that they are able to be more successful in the field of feature extraction by considering the spatial connections of features in the image.

In this article, the potential of implementing a capsule neural network to extract appropriate features from ultrasound images was investigated, in order to diagnose the type of tissue cancer in the thyroid gland. For this purpose, ultrasound images were firstly given as input to the capsule network, and then, the image features were extracted by the encoder part of the network. Subsequently, the feature reduction was performed using PCA method, and then the SVM classifier diagnosed the anomaly (benign or malignant).This work was implemented with Python language and achieved 98% accuracy. Correspondingly, this result was more significant than what has been done previously. In future works, we can use the combination of capsule network and CNN network to extract better features.

References

[1] J. Chi, E. Walia, P. Babyn, J. Wang, G. Groot, M. Eramian, J. Digit. Imaging 30 (2017) 477.

[2] H. Li, J. Weng, Y. Shi, W. Gu, Y. Mao, Y. Wang, W. Liu, J. Zhang, Sci. Rep. 8 (2018) 1.

[3] W. Song, S. Li, J. Liu, H. Qin, B. Zhang, S. Zhang, A. Hao, IEEE J. Biomed. Health Inform. 23 (2018) 1215.

[4] X. Li, S. Zhang, Q. Zhang, X. Wei, Y. Pan, J. Zhao, X. Xin, C. Qin, X. Wang, J. Li, F. Yang, Lancet Oncol. 20 (2019) 193.

[5] Z. Shi, H. Hao, M. Zhao, Y. Feng, L. He, Y. Wang, K. Suzuki, Multimed. Tools Appl. 78 (2019) 1017.

[6] T. Liu, S. Xie, J. Yu, L. Niu, W. Sun, IEEE International Conf. on Acoustics, Speech and Signal Processing (ICASSP). 5 Mar., 2017, IEEE.

[7] T. Liu, S. Xie, Y. Zhang, J. Yu, L. Niu, W. Sun, 14th International Symposium on Biomedical Imaging (ISBI 2017). 18 Apr., 2017, IEEE.

[8] S.Y. Ko, J.H. Lee, J.H. Yoon, H. Na, E. Hong, K. Han, I. Jung, E.K. Kim, H.J. Moon, V.Y. Park, E. Lee, Head & Neck 41 (2019) 885.

[9] O. Moussa, H. Khachnaoui, R. Guetari, N. Khlifa, Int. J. Imaging Syst. Technol. 30 (2020) 185.

[10] P. Qin, K. Wu, Y. Hu, J. Zeng, X. Chai, IEEE IEEE J. Biomed. Health Inform. 24 (2019) 1028.

[11] Q. Guan, Y. Wang, J. Du, Y. Qin, H. Lu, J. Xiang, F. Wang, Ann. Transl. Med. 7(7) (2019) 137.

[12] S. Sabour, N. Frosst, G.E. Hinton, Proc. Adv. Neural Inf. Process. Syst. 2017, pp. 3859-3869.

[13] A. Jiménez-Sánchez, S. Albarqouni, D. Mateus, in Intravascular Imaging and Computer Assisted Stenting and Large-Scale Annotation of Biomedical Data and Expert Label Synthesis 2018 Sep 16 (pp. 150-160). Springer, Cham.

[14] H. Kotadiya, D. Patel, Third Int. Cong. on Information and Communication Technology. Springer, Singapore, 2019.

[15] S.K. Jha, Z. Pan, E. Elahi, N. Patel, Expert Syst. 36 (2019) e12343.

[16] A. Aswathi, A. Antony, Second Int. Conf. on Inventive Communication and Computational Technologies (ICICCT). 2018. IEEE.

[17] M. Deepika, K. Kalaiselvi, Second Int. Conf. on Inventive Communication and Computational Technologies (ICICCT). 2018. IEEE

[18] G.U. Devi, E.M. Anita, Clust. Comput. 22 (2019): 11537.

[19] Y. Hao, W. Zuo, Z. Shi, L. Yue, S. Xue, F. He, Int. Conf. on Knowledge Science, Engineering and Management. Springer, Cham, 2018.

[20] H.A. Nugroho, E.L. Frannita, I. Ardiyanto, L. Choridah, J. King Saud Univ. Comput. Inf. Sci. 33 (2021) 323.

[21] M.S. Gharibdousti, S.M. Haider, D. Ouedraogo, L.U. Susan, Appl. Med. Inform. 41 (2019) 40.

[22] D. Dov, S.Z. Kovalsky, J. Cohen, D.E. Range, R. Henao, L. Carin, Machine Learning for Healthcare Conf. PMLR, 2019.

[23] X. Li, S. Zhang, Q. Zhang, X. Wei, Y. Pan, J. Zhao, X. Xin, C. Qin, X. Wang, J. Li, F. Yang, Lancet Oncol. 20 (2019) 193.Services Administration; 2003.

[24] M. Buda, B. Wildman-Tobriner, J.K. Hoang, D. Thayer, F.N. Tessler, W.D. Middleton, M.A. Mazurowski, Radiol. 292 (2019) 695.

[25] M.K. Patrick, A.F. Adekoya, A.A. Mighty, B.Y. Edward, J. King Saud Univ. Comp. Info. Sci. 2019. https://doi.org/10.1016/j.jksuci.2019.09.014

[26] T. Iesmantas, R. Alzbutas, International Conf. Image Analysis and Recognition, 27 Jun., 2018; Springer, Cham.

[27] T Zhao, Y Liu, G Huo, X Zhu, IEEE Access 7 (2019) 49691.

[28] A. Mobiny, H. Van Nguyen, International Conf. on Medical Image Computing and Computer-Assisted Intervention, 16 Sep., 2018; Springer, Cham.

[29] K.R. Kruthika, H.D. Maheshappa, Informatics in Medicine Unlocked 14 (2019) 59.

[30] T. Zhao, Y. Liu, G. Huo, X. Zhu, IEEE Access 7 (2019) 49691.; 2007, 133(3): 308–19.

[31] W. Zhang, P. Tang, L. Zhao, Remote Sens. 11 (2019) 494.

[32] H. Htun, M.M. Htay, S.T.Y. Myint, P.H.M. Wai, P.P. Soe, Thyroid 3(5) (2019).

[33] O. Faust, U.R. Acharya, K.M. Meiburger, F. Molinari, J.E. Koh, C.H. Yeong, P. Kongmebhol, K.H. Ng, Biocybern. Biomed. Eng. 38 (2018) 275.

[34] C. Liu, S. Chen, Y. Yang, D. Shao, W. Peng, Y. Wang, Y. Chen, Y. Wang, Med. Surg. 9(4) (2019) 642.

[35] N.B. Erichson, P. Zheng, K. Manohar, S.L. Brunton, J.N. Kutz, A.Y. Aravkin, J. Appl. Math. 80 (2020) 977.

[36] G. Douzas, F. Bacao, J. Fonseca, M. Khudinyan, Remote Sens. 11(24) (2019) 304.

[37] G. Li, D. Jiang, Y. Zhou, G. Jiang, J. Kong, G. Manogaran, IEEE Access 7 (2019) 11533.

[38] F. Du, Y. Sun, G. Li, G. Jiang, J. Kong, D. Jiang, Z. Li, Int. J. Wirel. Mob. Comput. 13(4) (2017) 306.

[39] G. Li, H. Wu, G. Jiang, S. Xu, H. Liu, IEEE Access 7(1) (2019) 23713.

[40] J. Qi, G. Jiang, G. Li, Y. Sun, B. Tao, Neural Comput. Appl. 32(10) (2020) 6343.