Effective Feature Selection on Transfer Deep Learning Algorithm for Thyroid Nodules Ultrasound Detection

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Abstract

Thyroid nodules (TNs) are discrete abnormalities located within the thyroid gland that are radiologically different from the surrounding thyroid tissue. Ultrasound is an accurate and efficient way to diagnose thyroid nodules. Recently, several methods of AI were proposed to improve the detection of thyroid nodules ultrasound images with good performances. However, in some cases related to the type or size of the dataset using machine or transfer deep learning methods alone is unable to achieve high accuracy and high specificity. Consequently, the addition of feature selection(FS) to the deep learning method enhances the results by reducing the high features and the time needed for training the dataset. This study proposes two deep-learning models for classifying thyroid nodule US images into two categories: benign and malignant. ResNet50 was the first model used to extract deep features from US images. The second model integrates ResNet50 and principal component analysis (PCA) for feature selection, intending to reduce dataset dimensionality while maintaining the greatest data variance possible before classification. The proposed model was created using a freely available dataset. The dataset consists of 800 images, 400 benign and 400 malignant. The suggested system was accessed based on accuracy, precision, recall, and F1 score. The detection accuracy for ResNet50 was 85%, while ReNet50-PCA was 89.16%. The combination of deep learning and FS techniques in this research produces an interesting diagnostic framework that can potentially increase efficiency and accuracy in thyroid cancer detection, especially in local healthcare centers.

Keywords: Feature Selection, Principal Component Analysis, Transfer Learning ResNet50, Thyroid Nodules, Ultrasound

اختيار فعال للميزات في نقل خوارزمية التعلم العميق لاكتشاف عقيدات الغدة الدرقية بالموجات فوق الصوتية

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الخلاصة:

عقيدات الغدة الدرقية (TNs) هي تشوهات منفصلة تقع داخل الغدة الدرقية وتختلف إشعاعيًا عن أنسجة الغدة الدرقية المحيطة. الموجات فوق الصوتية هي وسيلة دقيقة وفعالة لتشخيص عقيدات الغدة الدرقية. في الآونة الأخيرة، تم اقتراح عدة طرق للذكاء الاصطناعي لتحسين الكشف عن صور الموجات فوق الصوتية لعقيدات الغدة الدرقية مع أداء جيد. ومع ذلك، في بعض الحالات المتعلقة بنوع أو حجم مجموعة البيانات باستخدام الآلة أو نقل أساليب التعلم العميق وحدها غير قادر على تحقيق دقة عالية وخصوصية عالية. وبالتالي، فإن إضافة اختيار الميزات إلى طريقة التعلم العميق يعزز النتائج عن طريق تقليل الميزات العالية والوقت اللازم لتدريب مجموعة البيانات. تقترح هذه الدراسة نموذجين للتعلم العميق لتصنيف صور عقيدات الغدة الدرقية في لموجات فوق الصوتية إلى فئتين: حميدة وخبيثة. كان ResNet50 هو النموذج الأول المستخدم لاستخراج الميزات العميقة من صور

الموجات فوق الصوتية. يدمج النموذج الثاني ResNet50 وتحليل المكونات الرئيسية (PCA) لاختيار الميزة، بهدف تقليل أبعاد مجموعة البيانات مع الحفاظ على أكبر تباين ممكن في البيانات قبل التصنيف. تم إنشاء النموذج المقترح باستخدام مجموعة بيانات متاحة مجانًا. تتكون مجموعة البيانات من ٨٠٠ صورة، ٤٠٠ صورة حميدة و ٤٠٠ صورة خبيثة. تم الوصول إلى النظام المقترح بناءً على الدقة والإحكام والاستدعاء ودرجة F1. كانت دقة التصنيف لـ ReNet50هي ٨٥٪، بينما كانت 89.16% لـ ReNet50-PCA. إن الجمع بين تقنيات التعلم العميق واختيار الميزات في هذا البحث ينتج إطارًا تشخيصيًا مثيرًا للاهتمام لديه القدرة على زيادة الكفاءة والدقة في الكشف عن سرطان الغدة الدرقية، خاصة في مراكز الرعاية الصحية المحلية.

1. Introduction

The thyroid gland represents one of the most important glands within the endocrine system [1]. One prevalent endocrine disorder in adults is thyroid nodules [2]. yearly, the population's incidence of thyroid nodules increases [3], [4]. In Iraq, in Karbala governorate, thyroid cancer was the tenth-ranking cancer occurring in women in the years (2012-2020) in Al-Hussein Cancer Centre. makeup 2.70% of all cancer cases [5]. The prompt detection of a benign or cancerous thyroid nodule by the use of ultrasound is necessary for the diagnosis of thyroid cancer [6]. Thyroid nodules can be found and diagnosed using several modern imaging techniques, such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound. The best method is ultrasound imaging. Because it's affordable, non-invasive, radiation-free, safe, and readily available [7], [8], [9]. Measurements from ultrasounds are utilized to aid in the diagnosis of many different medical conditions [10]. A subfield of computer science called artificial intelligence (AI) enables programmers to construct software that can execute tasks usually carried out by people [11], [12], [13]. Machine Learning (ML) is part of AI algorithms where computers learn to self-improve existing insights and information [14], [15]. Deep Learning (DL) is part of ML algorithms with the ability to process more data, DL is one of the most popular algorithms used for classification and segmentation in radiology and medical imaging [16], [17]. Transfer learning is a technique that helps deep learning algorithms get beyond the limitation of having few training images when creating a robust model. By moving knowledge from a source task to a target task, this is achieved [18]. There have been several methods and techniques presented for the extensive research on thyroid cancer detection. In 2017, Chi et al. created a fine-tuned Google Net model to diagnose thyroid cancer lesions in US images. Features extracted from thyroid ultrasound images were fed into a Random Forest (RF) classifier, which accurately classified the images as cancerous or benign. The dataset consists of 428 thyroid ultrasound images with the size 560 × 360 from the open-access database and 164 images from a local database. The proposed model achieved 96.34% accuracy [19] . In (2019), Guo et al. suggested a DL method utilizing the ResNet18 model for thyroid nodule image classification. The dataset consists of 4509 thyroid nodule US images with a size (128×128) collected from different hospitals. To prevent overfitting of the deep learning model, this study used data augmentation. ResNet18's classification accuracy was 83.88% [20]. In (2023), Aboudi et al. suggested eleven CNNs and bilinear convolutional neural network (BCNN) methods, such as BCNN (ResNet50)2, to extract features from 447 US images of thyroid nodules. Subsequently, two classifiers, SoftMax and support vector machine, were applied. The proposed bilinear model obtained an accuracy of 87.72% and 90.34% using SVM and SoftMax, respectively [21].In (2024), Swathi et al. utilized quantum-inspired convolutional neural networks (QuCNet) that integrate quantum data processing with classical computation to enhance the efficiency and accuracy of thyroid nodule classification. The dataset consists of 333 thyroid nodule US images (102 benign and 231 malignant). The proposed model achieved an accuracy of 93.87% when tested on 98 images[22].The researchers in the previous studies introduced various algorithms to extract important information from the thyroid nodules' ultrasound images and obtained good results, but one of the gaps and limitations includes data size and imbalance handling; most studies mention using data augmentation techniques to increase and balance the number of images available for training.

In the proposed study, two models suggested ResNet50, and ResNet50-PCA for detecting thyroid nodules in US images. The first proposed model utilized transfer learning ResNet50 for feature extraction from US thyroid nodule images and then classifying them. The second model used feature selection (PCA) after the extraction of features from the ResNet50.

The major contributions of this research work are summarized as follows:

- Rearranged and labeled the data set into 800 images divided into 400 benign and 400 malignant by three Radiologists
- Use deep learning algorithms such as pretraind ResNet50 to extract the deep features from thyroid nodule US images.
- To increase efficient detection results combined pretrained ResNet50 methods with feature selection techniques such as PCA.

2. Methodology

This study aims to implement the transfer learning ResNet50 model to extract the deep features from thyroid nodule ultrasound images and then identify important features using the PCA technique. The proposed model would assist radiologists in the detection of benign and malignant thyroid nodule datasets. Figure 1 displays a small diagram representation of the proposed model procedures.

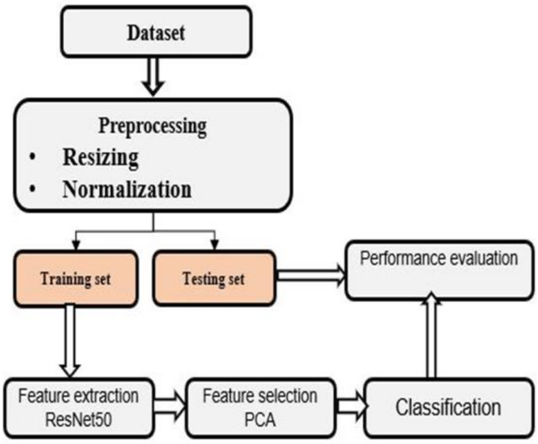


Figure (1): shows the suggested model.

2.1 Dataset

This study utilized freely available ultrasound images of thyroid nodules, provided by hospitals in Setif City, Algeria. The dataset is split into two classes Benign with 1472 ultrasound images, and Malignant with 1895 ultrasound images (https://www.kaggle.com/datasets/azouzmaroua/algeria-ultrasound-images-thyroid-dataset_auitd) [23]. To achieve optimal performance in the presented work, the dataset was rearranged due to the presence of unclear and highly noisy images. Besides the free data ground truth table, three experienced Iraqi radiologists established a second ground truth table for the 800 ultrasound thyroid nodule images. A total of 400 ultrasound images classified as benign and 400 images classified as malignant were carefully selected in JPG format. Fig (2) shows some thyroid nodule images after removing undesired areas or irrelevant details from the images, such as scan information, patient names, and noise from the background.

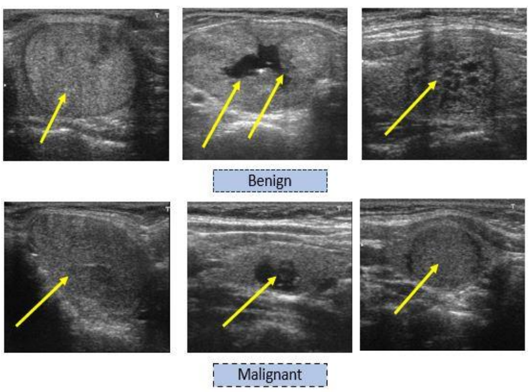


Figure (2): Thyroid nodule ultrasound images

2.2 Pre-processing

The data were preprocessed in preparation for the feature extraction stage. All Thyroid nodule ultrasound images were resized to (224, 224), thus the images have a uniform size that can be fed to ResNet50 in later stages of the model. The majority of CNNs used for image classification have been built and tested on images with sizes of less than (300x300) pixels [24]. Normalize all the pixel intensities in the thyroid nodule US images by dividing by the number 225.

3 Feature Extraction

Feature extraction is a process in which raw data is transformed into a set of features that effectively represent the underlying patterns or characteristics of the data. This transformation simplifies the data and makes it more suitable for processing by deep learning algorithms. The extracted features served as the starting point for the classification process. Feature extraction received special attention to provide a reliable and effective model efficiency. Feature extraction creates new features by transforming or combining the original ones, which is different from feature selection, and involves choosing a subset of existing features based on specific criteria such as relevance or complexity. In this research, features extracted from the ultrasound thyroid nodule images by using a deep-learning ResNet50 model.

3.1 ResNet50

ResNet50 is an abbreviation for a Residual Network design with 50 layers [25]. It is a very deep CNN architecture that has been trained on a large dataset of natural images and was designed to overcome the challenges of training very deep networks [26]. In this study transfer learning Residual Network (ResNet50) is first loaded with pre-trained weights from the ImageNet dataset to extract features. The first layers (convolution layers) are kept frozen and the fully connected layer is unfrozen and trained to perform classification tasks as shown in Fig (3). It consists of a sequence of residual blocks that contain multiple conv2D and skip connections to add input to the output block which enables ResNet50 to be trained without the issue of vanishing gradients.

4 . Feature Selection (PCA)

Feature selection is a dimensionality reduction technique, by selecting a subset of relevant features from the total original features and removing the irrelevant and redundant features. Feature selection reduces the number of features utilized in a model while maintaining the most significant and useful ones, thereby improving its performance. Feature selection has many advantages, including reduced data size, improved prediction accuracy, avoidance of overfitting, and faster execution and training due to easier understanding of variables [27][28]. Principal Component Analysis is an unsupervised learning technique for reducing data dimensionality. PCA can reduce high dimensions by selecting features with a high variance [29]. In this study, PCA is utilized to choose the most significant characteristics from a thyroid nodule ultrasound dataset. This work applied PCA for feature reduction after the extraction feature by ResNet50 and to classify thyroid nodule ultrasound images.

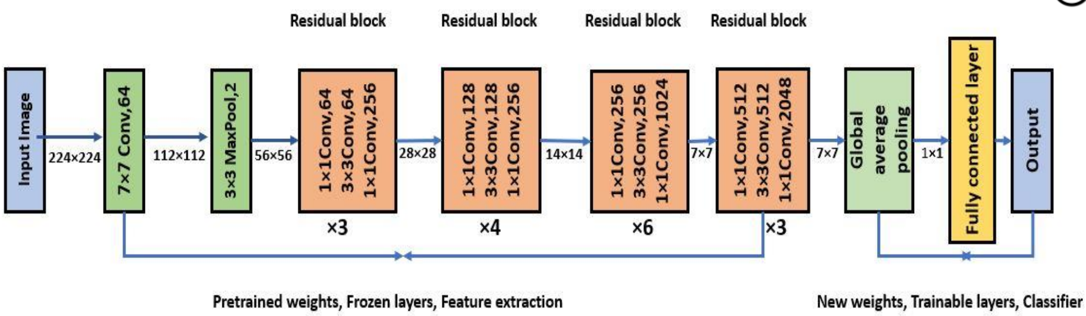


Figure (3): The proposed architecture of ResNet50.

5. Results

This study has proposed classifying 800 ultrasound thyroid nodule images as benign and malignant using ResNet50 features. To execute these models, The software installed on the laptop included Anaconda Navigator, Spyder, and Python 3.10.9, and many DL libraries such as TensorFlow, Keras, NumPy, cv2, glob, matplotlib, and sklearn installed from Anaconda prompt. The proposed models are achieved using a Dell laptop processor12th Gen Intel(R) Core(TM) i7-1255U and RAM 16 GB. The confusion matrix of the two models has been employed to determine the model's accuracy, F1 score, precision, and recall (sensitivity), as shown in Fig (4).

True positive (TP), False positive (FP), True negative (TN), and False negative (FN) values have been utilized in these formulas:

Accuracy: the ratio of the correct prediction to the total number of predictions.

$$\textbf{Accuracy} = \frac{\textbf{TP+TN}}{\textbf{TP+TN+FP+FN}} \times \textbf{100\%} \qquad ...(1)$$

Precision: the ratio of the true positive observations to the total predicted positive observations.

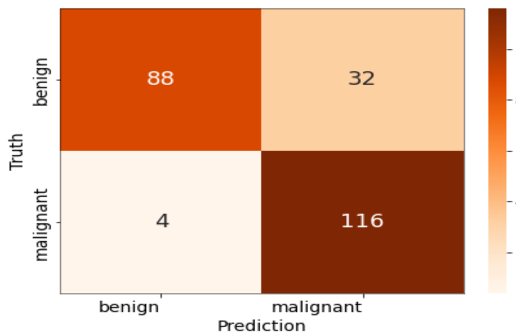
$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP+FP}} \times \textbf{100\%} \qquad ...(2)$$

Recall: the ratio of the correctly detected phenomena (True Positive) by the total number of true cases (True Positive + False Negative).

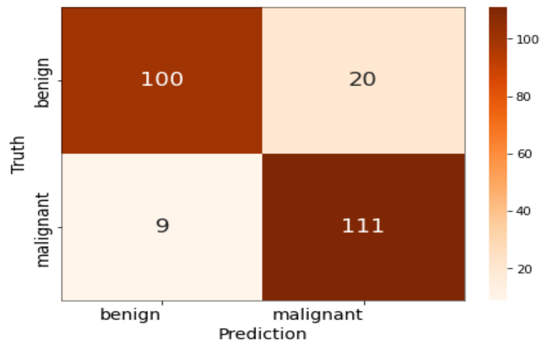
$$\textbf{Recall} = \frac{\textbf{TP}}{\textbf{TP+FN}} \times \textbf{100\%} \qquad ...(3)$$

F1 Score: the weighted average of Precision and Recall.

$$\textbf{F1Score} = \frac{\textbf{2} \times \textbf{(Recall} \times \textbf{Precision)}}{\textbf{(Recall + Precision)}} \times \textbf{100\%} \qquad ...(4)$$



(a) ResNet50



(b) ResNet50-PCA

Figure(4): Confusion matrix of the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) for the two models (a) ResNet50 and (b) ResNet50-PCA.

The ResNet50 model achieved the lowest accuracy of (85%). It is believed this result was obtained due to ResNet 50 dependence on pre-trained weights which means the model has been trained on a large dataset containing millions of labeled images which is different from the images of ultrasound thyroid nodules used in this work that means this model tested on data different from training data. Although the ResNet50 is considered a good very deep neural network model but needs a large number of data to give a high result. However, the model performance has been improved by adding a feature selection technique. The combined ResNet50 and PCA achieved the highest accuracy of (89.16%). This improvement indicates that PCA helps in reducing the dimensionality of the feature space by transforming the data into a lower-dimensional subspace while retaining most of the important information. This reduction can lead to more efficient computation and better generalization of the model. Moreover, PCA effectively eliminates noise and irrelevant information, focusing on the most significant aspects of the US thyroid nodule images. Tables (1,2) show the results of selected classifiers concerning accuracy, Precision, Recall, and F1-score for binary classes.

Table (1): The performance of the ResNet50.

Class	Precision	Recall	F1score	Accuracy
Benign	94%	83%	88%	
Malignant	85%	95%	90%	85%

Table (2): The performance of the ResNet50-PCA.

Class	Precision	Recall	F1score	Accuracy
Benign	96%	73%	83%	
Malignant	78%	97%	87%	89.16%

6. Discussion

This study suggests two models for classifying 800 thyroid nodule ultrasound images. These models aim to recognize benign and malignant thyroid nodules in US images. PCA feature selection methods have been used to assess ways of reducing computational complexity from unnecessary features. The model extracted the overall set of features using transfer learning ResNet50 algorithms.

The pre-trained CNN model had a good performance and high accuracy levels on classification (96.43%) when applied to 592 US image thyroid nodules [19]. Also, the ResNet18 model extracted features from variant datasets of US thyroid nodules and provided less accuracy (83.88%) in another study [20]. Combining ResNet50 features with a SoftMax and SVM classifier has further enhanced classification accuracy (87.72%, 90.34%) on the classification of 477 US images analyzed in this study [21]. In this work, the two models were implemented by using 800 US thyroid nodule images that were different from the data used in the previous studies. ResNet50 features in the first model were explored in terms of classification accuracy showing its highest performance to be (85%) accurate. The second model utilized PCA in combination with ResNe50 features, and it proved to provide superior results compared to the use of ResNet50 only. The combined ResNet5o-PCA model had its highest performance accuracy of (89.16%). Table 3 below shows previous methods used to classify thyroid nodule images compared to the proposed work.

Table 3 shows Previous methods compared to the proposed work.

Method	Data	Author	Accuracy
Pre-trained CNN-RF	592 thyroid nodule US images	In (2017), Chi et al.[19]	96.43%
ResNet18	4509 thyroid nodule US images	In (2019), Guo al.[20]	83.88%
BCNN(ResNet50)2-SoftMax BCNN(ResNet50)2-SVM	447 thyroid nodule US images	In(2023),Aboudi et al.[21]	87.72% 90.34%
ResNet50, ResNet50-PCA	800 thyroid nodule US images	Proposed model	85%, 89.16%

7. Conclusion

In conclusion, this study developed thyroid nodule classification models by employing ResNet50 for feature extraction and PCA for feature selection. Although the ResNet50 is considered a good deep-learning theory in the image classification field, it has been trained on a large dataset containing millions of labeled images. In this study, transfer learning of ResNet50 knowledge used to classify a limited number of medical images makes ResNet50 alone insufficient to achieve high accuracy. To overcome these obstacles, adding feature selection to ResNet50, such as PCA, proved effective in increasing the outcome. The deep learning technique can provide an instantaneous solution to aiding in the detection process, hence limiting the spread of thyroid cancer. For future works, collect more data from different Iraqi hospitals for training and testing these models for better outcomes, further improving and generalizing the proposed model.

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