Classification Of Thyroid Nodules from Ultrasound Images using Residual Network (Res Net)

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Abstract

Thyroid nodules, which are characterised as aberrant thyroid cell growth, is due to heavy intake of iodine, or thyroid degeneration or the inflammation, and some diseases. Despite the fact that thyroid nodules are mostly benign, the likelihood that they are malignant rises noticeably every year. The labour of medical practitioners are reduced and optional fine needle aspiration, surgical excision are avoided. Firstly, FNA results are occasionally ambiguous, which means they do not always say for sure whether a nodule is benign or cancerous. This can happen when there aren't enough cells in the FNA sample or when the cellular properties are unclear. Uncertainty and the need for extra testing or repeated biopsies can be brought on by indeterminate results, which can be expensive and stressful. A number of studies have been done to identify thyroid nodules with the use of image recognition analysis based on deep-learning. A new deep learning architecture is provided in this study. It reliably identifies the benign and malignant thyroid nodules among given dataset. First, we have considered both Vgg19 and Resnet50 models and they were pre trained on the Image Net database and then trained using the thyroid ultrasound image dataset and tested with the testing dataset. In comparison, we have achieved greater accuracy using Resnet50 model rather than Vgg19. The trained model has now able to classify the thyroid nodules into different categories like normal, benign and malignant. A website is also developed which can predict the type of nodule using the accurate model. Overall, the proposed model demonstrated that ultrasound images and deep learning may be used to distinguish between benign and cancerous thyroid nodules with a 75% accuracy and

Keywords: Resnet50, VGG19, benign, malignant, normal.

1. Introduction

Thyroid disease is one of the most important poorly understood, under detected diseases. Diabetes and disorders of the thyroid gland are the two endocrine illnesses that are most prevalent globally, in accordance with the World Health Organization (WHO). A tiny, butterfly-shaped gland called the thyroid is found near the base of the neck, right below the Adam's apple. It produces thyroid hormones, which play a critical part in controlling a number of body activities. An imbalance in the production of hormones results from a variety of illnesses known as thyroid diseases that alter the structure or function of the thyroid gland .Hypothyroidism and hyperfunction hyperthyroidism affect, respectively, 2% and 1% of people. Men outnumber women by an amount that is around one eighth. Potential causes of hyper- and hypothyroidism include disorders of the thyroid gland, pituitary gland, and hypothalamus. As a result of deficiency in dietary iodine, frequency of goitre or active thyroid nodules may be increases, up to 15%, in some regions.[21]

Endogenous antibodies can mess with the thyroid gland, which can house a variety of cancers and be dangerous (autoantibodies). According to specialists, limiting disease progression and even death depends on early disease identification, diagnosis, and management. Physical examinations, blood tests to check hormone levels, imaging scans, and occasionally a thyroid tissue sample are used to diagnose thyroid problems. Depending on the exact problem, there are several treatment options available,

including drugs, radioactive iodine therapy, surgery, or a combination of methods. The possibility of effective therapy for a range of disorders is increased by early detection and differential diagnosis. Despite many attempts, clinical diagnosis is usually seen as a very hard task. Thyroid disorder is a quite possibly of the most unavoidable sickness all over the planet, and it is generally avoidable by reducing intake of iodine quantity, there are several factors that could affect besides iodine intake. Actually, thyroid organ is an endocrine organ. Endocrine organs generally secretes synthetics. Then makes it to go through Flow of framework. As said above, the secreted compounds of thyroid organ are forced to help in ingestion, staying aware of the body wet, changed, and etc.

From the Thyroid prescriptions like T3, T4 and TSH, it is easy to get in detail of thyroid activity [25]. Thyroid disturbance is requested into two sorts:

- hypothyroidism
- hyperthyroidism.

Data mining is a semi-mechanized technique useful in getting associations with enormous datasets. Data mining techniques such as Classification, Clustering, Association Rule Mining, Predictive modelling, feature Selection are some of the techniques that can be applied to thyroid data and extract the valuable information required for the analysis of thyroid nodules. It's crucial to remember that the quality and amount of the dataset, as well as the level of experience of the data mining practitioners, determine how successfully data mining algorithms perform thyroid-related analyses. In order to guarantee accurate diagnosis and sensible treatment choices, the interpretation of results should always be done in cooperation with healthcare specialists. Artificial Intelligence (AI) and profound learning calculations can be the most mind-blowing answers for the issues. Issues may be are challenging to settle. Grouping is an information extraction method (AI) used to foresee and distinguish numerous illnesses, for example, thyroid sickness, which we explored and ordered here since AI calculations assume a critical part in characterizing thyroid infection and on the grounds that these calculations are of high performance, productive and also beneficiary in characterization. Albeit, is useful in PC learning also in computerized reasoning that are present in medication traces, there also has another development to consider in the requirement section for AI related medical care arrangements. Accordingly, examiners anticipate that AI will become typical in medical care sooner rather than later. However, ultrasound diagnosis mainly depends on the knowledge and judgement of doctors, which could lead to misdiagnosis. A deep learning model was utilized to classify harmless and dangerous thyroid knobs.

2. Approach

2.1 Background Work

Various approaches related to thyroid nodules are proposed to improvise the accuracy of detecting Thyroid nodules. Ultrasonography become a essential tool in diagnosis of thyroid nodule. Computer based Diagnosis using Ultrasonography is an approach for diagnosing thyroid using computer-aided diagnosis. The main objective of this approach is to evaluate, examine the conduct of CAD system among nodules of thyroid and also to know its importance in thyroid diagnosis, improvement of thyroid nodule detection. Computer aided diagnosis is combined with Ultra sound systems. CAD is a software, its functionality is to find the features of image based on its composition of mass. It is helpful in extracting exact features. It's features are extracted and examined automatically using CAD software and classified them into benign and malignant based on the extracted features. CAD examines the ultra sound image and automatically selects its area of interest based on its mass composition, which plays key role in determining benign or malignant. On the other side professional radiologists uses grey-scale matrix method to extract the features, radiologists manually draws there areas of interest on ultra sound image and examines it. Examination is also done with combination of CAD system and radiologist. Performance in all the cases were examined using accurate rate, PPv's, NPv's, specificity and precision. And it is found that the performance of radiologist with CAD system is found effective than CAD system alone or radiologist alone. However, CAD system didn't evaluated calcification [28]. Deep convolutional neural network (CNN) is used, to evaluate the diagnostic performance, and is compared with the performance evaluated by radiologist. ultra-sound image is not capable of categorizing thyroid

nodule accurately. So in addition to it CNN is introduced, as that it maximises the potential of feature extraction and makes decision taking process efficient. Around 14,320 of ultra sound image of thyroid nodules are given, as input for the development of an algorithm. Ultra sound image goes through acquisition process. ROI boundaries are drawn to images, and normalised. These images are given as input to algorithm. For improvement in efficiency, various pretrained CNN's are used and finely tuned with each CNN having independent decision making, and majority opinion is gathered. It can be done using classification ensemble, by collecting probabilities provided by each CNN, and on an average it gets new probability with a final decision to classify nodule into benign or malignant. Clinically tested thyroid nodules are compared with classification ensemble, and found that ensemble CNN performance is efficient in classifying thyroid nodules [29]. Before classifying a thyroid gland, into benign or malignant. 'Automatic measure of thyroid gland' measures the anteroposterior of thyroid gland in ultrasound images. Automatic Measurement of Thyroid Gland automates the diagnosis of thyroid by measuring its anteroposterior diameter, which is used to assess the unnecessary growth of thyroid called, Goiter. It plays a major role in determining the level of harmfulness of Thyroid nodule. B-mode ultrasound image were taken into consideration. First it detects the outlines of Thyroid nodules, it can be done by extracting a image using grey-scale level method, these levels are categorized into 'z' different grey levels, the part of hyperechoic region is identified. The next step includes vertical scanning and retrieving a total of k successive strips, weighted sum is calculated using some quantitative formulas, rate of change between successive strips are calculated. And based on these resulting conditions, outlines are located internally and externally on identification strip. Image regions defined by radiologist and the proposed methods are compared and found that the performance of proposed method is similar to that of professional radiologists. It produces high accuracy in large number of cases, it can reduce the failures in diagnosis of Thyroid nodules [30].Gender and racial/ethnic differences in thyroid cancer incidence also have an impact on how people can access and use healthcare. Another approach is that, demographics and tumour characteristics makes possible to look into thyroid cancer incidence rates. For this purpose, it uses data that is collected from thyroid cases nearly about 48,403 (diagnosed in 1980 up to 2005). The rates varied Based on histologic type, race and sex. At this time there were about papillary thyroid cancers nearly 39,706 were identified and were the focus of further analyses. Females experienced the fastest growth in papillary carcinoma rates. However, they did so more slowly than individuals with a starting stage and small sized tumours. Increasing rates of very tiny (2 cm) papillary carcinoma between 1992 and 1995 were responsible for half of the overall increase in papillary carcinoma rates. Medical surveillance or more accurate detection methods cannot fully explain the reported increase in papillary thyroid cancer rates. Therefore, it's critical to hunt for further justifications. All these scenarios, motivated for present algorithm that is Ultrasound image classification that is based on Thyroid nodules.
This strategy has certain shortcomings even though it produced a favourable outcome. First off, there aren't enough images accessible for training and testing, and there aren't any multicentre data. Second, several algorithms may be used to classify thyroid nodules in a more thorough manner. Clinically, thyroid nodules can be separated into benign nodules as well as follicular adenomas, while thyroid nodules that are malignant can be separated into Medullary carcinomas that are papillary, follicular, etc. finally results are regarding ultrasound scans (static), which is a crucial final point, and we should think about ways to help doctors more effectively in a real clinical setting.

2.2 Methodology And Implementation

Two algorithms namely VGG19 and ResNet50 are employed to train the model. The accuracy of the algorithms is compared and the best one is chosen to train the model.

Dataset: Collected around 2289 ultrasound images of thyroid nodules of JPG format from the Kaggle and afterward pre-trained them for feasible and optimal classification. Among them, 1930 images of the dataset are saved in a folder and named as train which should be treated as the training set and 359 images are saved in a folder named as test which should be treated as the testing set.

Description of data: The mode of this image dataset is categorical. The whole dataset is categorized into three different folders named normal, benign and malignant.

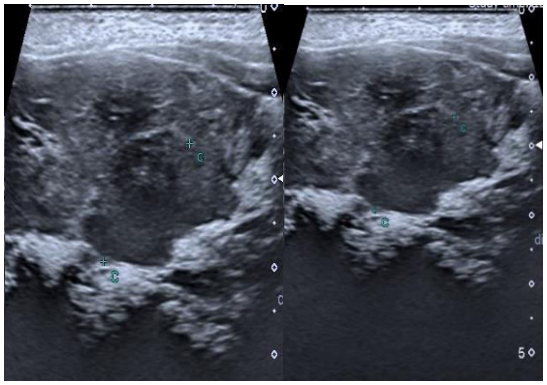

Figure 1. Noraml thyroid nodule ultrasound images

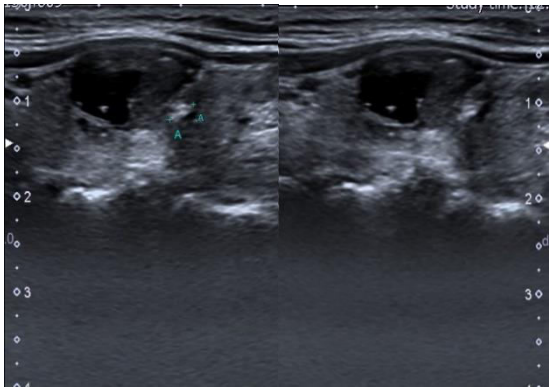

Figure 2. Benign thyroid nodule ultrasound images.

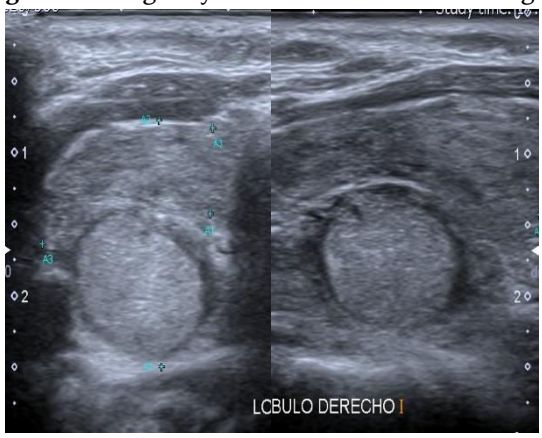

Figure 3. Malignant thyroid nodule ultrasound images

Data Pre-processing: Data Pre-processing include removal of unwanted frames, portions and text in the images for better classification using some pre-defined functions and built-in modules of Python.

Splitting the data: As we mentioned earlier that 2289 images were gathered from Kaggle, in those images 1930 have used for training the model and rest of the images used for testing purpose Since the dataset mode is categorical, the splitting of data happened at the directory level by placing different categorical images in their respective labelled folder or directory and thus splitting had not done at the code implementation level.

Model Training: Firstly, we have used VGG19 model an existing model which is not mentioned in the proposed system. In order prove that the proposed algorithm gives better accuracy compared to existing model, we have used VGG19. Then we have trained the dataset using ResNet50 which is a proposed algorithm.

Model Evaluation: In this Evaluation phase, we calculate the accuracies of different models that we have used to classify our dataset. Based on the evaluation results, we prove that the proposed model works better than the existing model.

3. Findings

3.1 *Dataflow Diagram*

A data flow diagram (DFD) gives an insight about the flow of information for any process or system of a software.

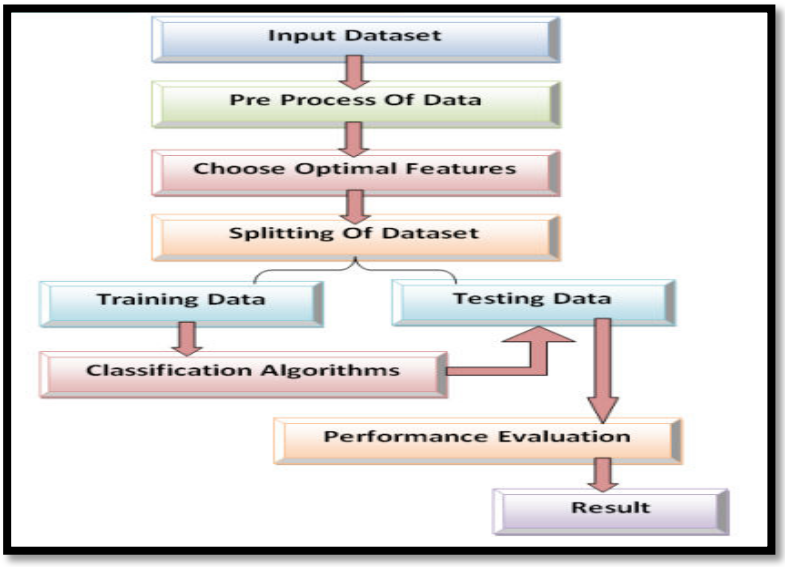

Figure 4. Data flow diagram of the system

Two algorithms namely VGG19 and ResNet50 are employed to train the model. The accuracy of the algorithms is compared and the best one is chosen to train the model.

3.2Vgg19

VGG19 is the 19 layers deep convolutional neural network. This algorithm is used for recognizing the large-scale images. It is pre trained on the ImageNet database and able to classify the objects into more than 1000 different categories. It is 19 layers deep which consists of layers like convolutional, ReLu, pooling, fully connected and SoftMax. The input that should be given to the algorithm is of size (224,224) and a three-channel image should be provided.

```
base_model = VGG19(input_shape=(224,224,3), include_top=False, weights="imagenet")
for layer in base_model.layers:
    layer.trainable=False

model=Sequential()
model.add(base_model)
model.add(Dropout(0.5))
model.add(Flatten())

model.add(BatchNormalization())
model.add(Dense(2048,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.5))

model.add(Dense(1024,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(3,activation='softmax'))
OPT    = tensorflow.keras.optimizers.Adam(lr=0.001)
METRIC = tensorflow.keras.metrics.AUC(name = 'auc')

model.compile(loss='categorical_crossentropy',metrics=METRIC,optimizer=OPT)

model_history=model.fit(train_dataset1,validation_data=valid_dataset1,epochs =50,callbacks = callback_list)
```

Figure 5. Implementation of VGG19

The Figure 5 contains the implementation of VGG19 model.

- Initially the model is pretrained on the ImageNet database which consists of millions of images of multiple categories.[23,27]
- In further steps, the hidden layers of the algorithm like activation layer, batch normalization layer, SoftMax layer are added to the model.
- The rate of learning for the model is set as 0.001.
- The cross entropy is employed as the loss function to obtain the consistent results.
- Finally, the model trained using the training dataset by performing 50 epochs.

3.3Resnet50

Resnet50 is one of the efficient deep convolutional neural networks which consist of 50 layers. It is the deep residual network[27]. Residual neural network is one of the types of Artificial Neural Network in which continuous blocks stacks up and forms a layered network. The major problem faced with the deep neural networks are it is difficult to train the model whereas by using Resnet the problem can be tackled. The more the layers are added to the network the more the complex the model becomes but if there are more layers in the network then individual layers can be trained on various factors and the overall accuracy of the model can be improved. These causes the problem of exploding gradient. This exact problem can be tackled by using the skip connections which is the core foundation of Resnet architecture[22].

```
#Model
base_model = ResNet50(input_shape=(224,224,3), include_top=False,weights="imagenet")
for layer in base_model.layers:
    layer.trainable=False
model=Sequential()
model.add(base_model)
model.add(Dropout(0.5))
model.add(Flatten())
model.add(BatchNormalization())
model.add(Dense(2048,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(1024,kernel_initializer='he_uniform'))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(3,activation='softmax'))
# Model Compile
OPT    = tensorflow.keras.optimizers.Adam(lr=0.001)
METRIC = tensorflow.keras.metrics.AUC(name = 'auc')
model.compile(loss='categorical_crossentropy',metrics=METRIC, optimizer=OPT)
model.summary()
model_history=model.fit(train_dataset,validation_data=valid_dataset,epochs = 50, callbacks = callback_list)
```

Figure 6. Implementation of Resnet50

The figure 6 demonstrates the implementation of the ResNet50 algorithm.

- Initially the model is pretrained on the ImageNet database which consists of millions of images[23]. After the model is pretrained, it is now capable of classifying items into more than 1000 different categories of images.
- After the model is pretrained, the essential layers of the algorithm such as Normalization layer, Dropout layer, Activation, Dense layers are added to the model[25].
- The rate of learning of the model is set as 0.001 and the same the cross-entropy technique is employed as the loss function to output the predicted values with consistency.
- Summary of the model is viewed after pre training the model which is used to display the total number of parameters and the corresponding trainable and non-trainable parameters

out of them.

- The model is set to compile with the training dataset for 50 times to improve the overall accuracy of the model.

4. Flowchart

In this paper, we have gathered 2289 ultrasound images of thyroid nodules of JPG format from the Kaggle and afterward pre-trained them for feasible and optimal classification. Among them, 1930 images of the dataset are saved in a folder and named as train which should be treated as the training set and 359 images are saved in a folder named as test which should be treated as the testing set. Between the training and testing datasets, we made sure that there was no overlapping[26]. If any overlapping occurs, the accuracy increases so there is no point in training the dataset and that's not proper way to train the model. The principal work is as per the following. the ResNet50 model, joined with move learning, was utilized to arrange typical(normal), benign which are harmless and malignant which are dangerous thyroid knobs.

Typically, the shape, the texture and colour feature extraction are the considerable things that comes under any image feature extraction[22]. These are the features that can depict images from various views. To elucidate the shapes of objects in images their features are mostly considered. To illustrate the shape, the area dilation, perimeter convexity and the form parameter were embraced along with the extracted features of thyroid nodules[22]. Perhaps, these features may be the most apt interpretation of the regions shape but they might not be the most perfect explanation of the characteristics of the target portions.

The work process of thyroid nodule image dataset classification is done with ResNet50. The Layers and the adaptive pooling depict the course of image by feature extraction and exploration with ResNet50. With the addition of layers, the key features extricated by the algorithm which turned out to be more dynamic. AUC, the acronym for area under the curve and other examination indexes were utilized to test the effect of training model classification.

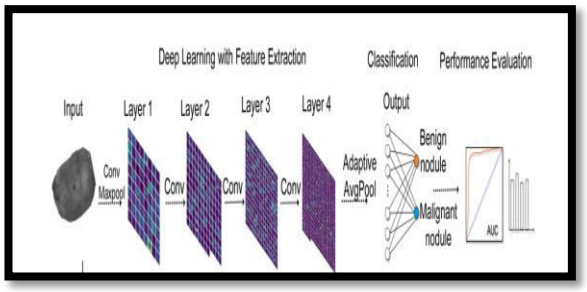

Figure 7. Pictorial representation of proposed system

5. Evaluation Metrics

Evaluation is the process of measuring the quality of a model we have built by using some evaluation metrics like accuracy of the model and ROC curve[23]. We have built two models by using VGG19 and ResNet50 respectively. The performance of both the models are evaluated based on the evaluation metrics and the best one is selected and used for further classification of thyroid nodules.

Now in an orderly we go through each and every one of the algorithms by evaluating the model using the conventional sklearn module in which we use the metrics function to evaluate the model.

6. Results

As we trained our dataset on two deep learning models, ResNet50 has given more promising results in terms of accuracy and precision over VGG16. The accuracy produced by ResNet50 is 75% while the accuracy of VGG16 is 55%. Residual network or ResNet was an important development that has transformed the training of deep convolutional neural networks for tasks related to image

classification. Earlier, Resnet had 34 layers and used 2-layer blocks, other improved versions, like the Resnet50, made the use of 3-layer bottleneck blocks to guarantee enhanced accuracy and less training time. This is the reason why the ResNet50 has given better accuracy. A simple website is developed where end users can upload ultrasound Thyroid nodule image to know whether it is malignant or benign, so that the layman can access the results of our proposal. We have successfully integrated our trained model with the website using Flask library.

7. Conclusion

A lifelong medical problem thyroid, which is an abnormal development of thyroid cells, requires continual management. Both the doctor and the patient gains from finding the nodules and identifying them as benign or cancerous. Here is the application of our proposal, Deep Learning-based Ultrasound Image Classification of Thyroid Nodules. This proposal can assist the physician in determining the thyroid nodule's level of malignancy and in providing the patient with better treatment recommendations. A doctor can assess whether there are numerous nodules. When using fine-needle aspiration technology, it serves as a guidance. only getting to know, how cancerous a specific thyroid nodule isn't sufficient, proper care must also be taken to cure it as well and monitoring thyroid nodule growth is also important. The interpretability of the ultrasound images is very poor and it would be very challenging for doctors to believe the output of the model and continue with further diagnosis. Data obtained from the Algeria's hospitals exactly Setif city, is considered for this proposal. The proposed, enhanced, and normalized images or dataset was provided to the Resnet50 model and VGG model as a training, testing, and validation set.

There are 48 convolution layers that also includes maxpool , average pool layer in the Resnet50 model. Images are traversed through these layers. After maxpool and Average Pool layer, Image features are automatically extracted, and results in the predicting, whether a nodule is benign or cancerous or a normal thyroid. A deep convolutional neural network- Visual Geometry Group, consists of 19 convolutional layers. Accuracy, on classifying images as benign, malignant, normal thyroid by using VGG is generated. Among Resnet50 and VGG, the one with more accuracy is considered.

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