



AN HOSPITAL APPLICATION INVOLVING DEEP LEARNING METHODOLOGY FOR DETECTING SIX DIFFERENT TYPES OF THYROID DISEASES

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Abstract-Thyroid is arguably one of the most important parts of your body. As part of the endocrine system, this small gland in your neck secretes thyroid hormone, which is responsible for directing all your metabolic functions—that means controlling everything from digestion to mood to energy. When the thyroid malfunctions, it can affect every facet of your health. In that thyroid disease is a major cause of formation in medical diagnosis and in the prediction, onset to which it is a difficult axiom in the medical research. Thyroid gland is one of the most important organs in our body. The secretions of thyroid hormones are culpable in controlling the metabolism. Typically, visual examination and manual techniques are used for these types of a thyroid disease's diagnosis. This manual interpretation of medical images demands high time consumption and is highly prone to mistakes. Thus, In this project we develop and apply a novel deep learning architecture to effectively detect and identify the presence of five different thyroid diseases such as Hyperthyroidism, Hypothyroidism, Thyroid cancer, Thyroid nodules, Thyroiditis.

Keywords-Thyroid, National Institute Of Health, Thyroiditis, Mayo clinic, Grave's Disease, National Cancer Institute, Thyroid cancer, Hypothyroidism, Hyperthyroidism, Thyroid nodules, Thyroxine hormone

I. INTRODUCTION

In our day-to-day life we lead a life in which there are many types of diseases which can both be treated and some diseases cannot be treated one among the curable diseases is thyroid. Thyroid is a disease which is caused due to imbalance in the levels of secretion of thyroxine hormone secreted by thyroid glands present in our human body. when there is imbalance in thyroxine hormone it leads to some of the diseases, The most common thyroid disorders and what we know about the causes of each. If you think you may have one of the conditions below, voice your concerns to your doctor so you can be appropriately screened and get your condition under control before it's too late.

Hypothyroidism

Hypothyroidism is also called as underactive thyroid. This type of thyroid disease is caused due to production of low amount of thyroid hormone, therefore, all of your body's important processes get slowed down. Weight gain, decreased appetite, fatigue, dry skin, and heavy periods are all hallmark symptoms of hypothyroidism, as your body's cells are unable to work at their normal level of efficiency.

The most common cause of an underactive thyroid is thyroiditis, swelling of the thyroid gland (see below), according to the National Institutes of Health.

Thyroiditis

Thyroiditis causes thyroid inflammation. Thyroiditis can cause pain in the thyroid, or lead it to produce too much or too little thyroid hormone. Some may start to develop symptoms over time, after the inflammation has been impacting the thyroid for a while. The most common cause of thyroiditis is an autoimmune disease, which causes the immune system to mistakenly send antibodies to attack the thyroid gland. The specific one most frequently associated with thyroiditis (and that then causes hypothyroidism) is called Hashimoto's disease

Hyperthyroidism

Hyperthyroidism is when your thyroid is overactive and releasing too many hormones. Weight loss, increase in appetite, diarrhea, anxiety, and rapid heartbeat are all signs of hyperthyroidism.

The most common cause of hyperthyroidism is an autoimmune disease called Graves disease, where the body attacks the thyroid and causes it to overproduce thyroid hormones. Postpartum thyroiditis can also cause hyperthyroidism, as can thyroiditis caused by an infection in the body.

Thyroid nodules

A nodule is simply an abnormal growth of cells, which can be either solid or fluid-filled. Thyroid nodules are quite common. Most are benign, he adds, and present without symptoms. The only way you'll know you have it is if you notice a lump in your neck or it gets picked up during a routine health exam or scan.

Thyroid cancer

According to the National Cancer Institute, there were an estimated 62,450 new cases of thyroid cancer in 2014. The rate has been increasing in recent years, which experts estimate is partly because new technologies have made it easier to detect. The full reason for this increase, though, is not yet known. The good news is that thyroid cancer is usually very treatable, and the survival rates are high.

Thyroid cancer often presents without symptoms and just causes a goiter or nodules that usually will not impact the thyroid's function or cause any pain in the early stages. As it progresses and cancerous nodules grow, you may experience pain in the neck, difficulty swallowing, or a hoarse voice.

II. LITERATURE SURVEY

In this paper [1] We aimed to propose a highly automatic and objective model named online transfer learning (OTL) for the differential diagnosis of benign and malignant thyroid nodules from ultrasound (US) images. Methods: The OTL method combined the strategy of transfer learning and online learning. Two datasets (1750 thyroid nodules with 1078 benign and 672 malignant nodules, and 3852 thyroid nodules with 3213 benign and 639 malignant nodules) were collected to develop the model.

[2] Age-specific thyroid phantoms corresponding to 5, 10, 15 years-old and the adult case have been designed and manufactured with a 3D printer. Reference measurements of the counting efficiency have been carried out for thyroid in vivo monitoring of ^{131}I with all these phantoms. These measurements were performed for the emergency mobile units of IRSN. The full efficiency curve, between 29 and 1000 keV, was then obtained by Monte-Carlo calculations and validated by comparison of a large set of measurements.

[3] This study presents a rapid and low-cost method to detect thyroid dysfunction using serum Raman spectroscopy combined with support vector machine (SVM). The serum samples taken from 34 thyroid dysfunction patients and 40 healthy volunteers were measured in this study. Tentative assignments of the Raman bands in the measured serum spectra suggested specific biomolecular changes between the groups. The average accuracy of 30 discriminant results reached 82.74%, and the average optimization time was 0.45 s. 40 normal thyroid function subjects and 34 abnormal thyroid function patients were analyzed by their serum Raman spectra.

[4] We compared a conventional PET-CT scanner (Siemens Biograph TruePoint TrueV) with and without resolution modeling (RM) image reconstruction with a high resolution research tomograph (HRRT) in order to assess the utility of conventional scanners for brain scanning. A modified Esser phantom and 6 neurofibromatosis 2 (NF2) patients with vestibular schwannomas (VS) were scanned using both scanners. The phantom was filled with fluorine-18 (40 MBq, 4:1 contrast ratio) and scanned for 60 min on separate occasions. Patients were injected with ~200 MBq of [^{18}F] fluorodeoxyglucose (FDG) and [^{18}F] fluorothymidine (FLT) on separate occasions and scanned for three consecutive 30 min periods moving between scanners.

[5] Temporal Enhanced Ultrasound (TeUS), comprising the analysis of variations in backscattered signals from a tissue over a sequence of ultrasound frames, has been previously proposed as a new paradigm for tissue characterization.

[6] In clinical practice, an overwhelming majority of biopsied thyroid nodules are benign. Therefore, there is a need for a complementary and noninvasive imaging tool to provide clinically relevant diagnostic information about thyroid nodules to reduce the rate of unnecessary biopsies. The goal of this study was to evaluate the feasibility of utilizing comb-push ultrasound shear elastography (CUSE) to measure the mechanical properties (i.e., stiffness) of thyroid nodules

[7] Fine-needle aspiration (FNA) remains the gold standard for the diagnosis of thyroid cancer. However, currently a large number of FNA biopsies result in negative or undetermined diagnosis, which suggests better non-invasive tools are needed for the clinical management of thyroid cancer. Spectral-based quantitative ultrasound (QUS) characterizations may offer a better diagnostic management as previously demonstrated in mouse cancer models *ex vivo*.

[8] Cancer, as the most challenging part in the human disease history, has always been one of the main threats to human life and health. The high mortality of cancer is largely due to the complexity of cancer and the significant differences in clinical outcomes. Therefore, it will be significant to improve accuracy of cancer survival prediction, which has become one of the main fields of cancer research.

III. PROBLEM STATEMENT

Prediction of thyroid diseases presence by manually checking the reports by a number of doctors leading to mistakes causing life losing disadvantages.

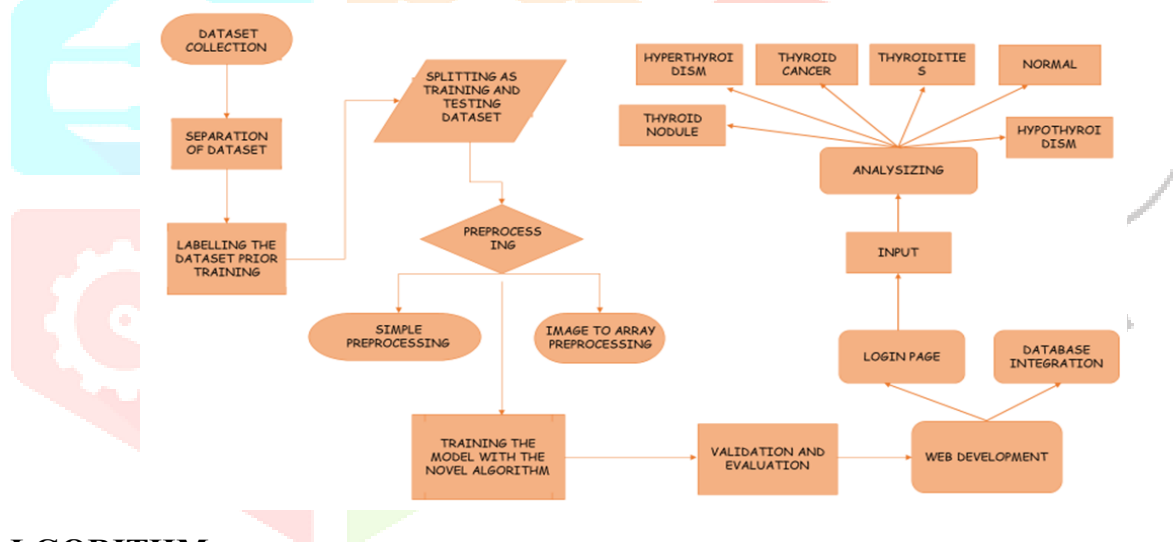
Leads to loss of life and increased risk.

Time consuming

IV. ARCHITECTURE

In this project, we are going to determine presence of thyroid diseases. By this project, we can able to determine the presence of thyroid diseases in the CT images or x-rays. So, initially the first step will be dataset collection where we will be collecting dataset such as CT images or x-rays which are used by the laborites to analysis the presence of thyroid diseases from various resources through internet. After that, we will be splitting those datasets into different categories that is we will be splitting the dataset into training and testing dataset.

In training datasets, we will be using the dataset for training the module whereas testing dataset is used to evaluate the model when it is been completely ready. So training dataset first undergoes the process called dataset augmentation, where the dataset is multiplied into many datasets then it will undergo the process called preprocessing, which is to make all sizes into single size. We train that datasets by extracting the features using a novel deep learning architecture. It undergoes a process called optimization which will optimize the model and loss minimization which will reduce the noises generated during training. In the last it will be undergoing a process is called model seriation which will be evaluated after generating model using the testing dataset and predict the presence of thyroid diseases. A web application using a javascript framework reactJS will also be developed in which an input scanned image will give the output of the type of thyroid disease saving a lot of time and money invested by the patients. Thus, this method provides an effective and cheap method to determine the presence of thyroid diseases than the methodologies used nowadays.

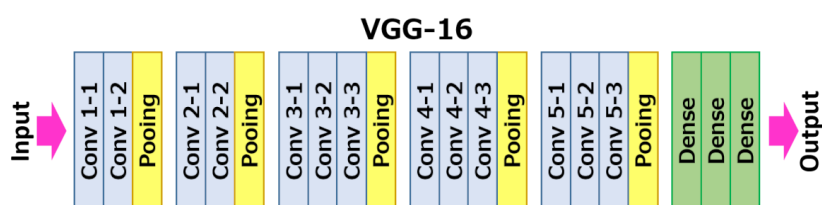


V. ALGORITHM

In order to train the model, we will be using novel algorithm. The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. The novel architecture was trained for weeks and was using NVIDIA Titan Black GPU's.

ImageNet is a dataset of over 15 million labelled high-resolution images belonging to roughly 22,000 categories. The images were collected from the web and labelled by human labellers using Amazon's Mechanical Turk crowd-sourcing tool. Starting in 2010, as part of the Pascal Visual Object Challenge, an annual competition called the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) has been held. ILSVRC uses a subset of ImageNet with roughly 1000 images in each of 1000 categories. In all, there are roughly 1.2 million training images, 50,000 validation images, and 150,000 testing images.

ImageNet consists of variable-resolution images. Therefore, the images have been down-sampled to a fixed resolution of 256×256 . Given a rectangular image, the image is rescaled and the input to conv1 layer is of fixed size 224×224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configurations, it also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2 pixel window, with stride 2, cropped out the central 256×256 patch from the resulting image. The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks.



VI. RESULT

To begin with, testing of the trained model, we can split our project into modules of implementation that is done.

Dataset collection involves the process of collecting different thyroid diseases dataset.

Various datasets were collected and one example among the collected dataset can be found below

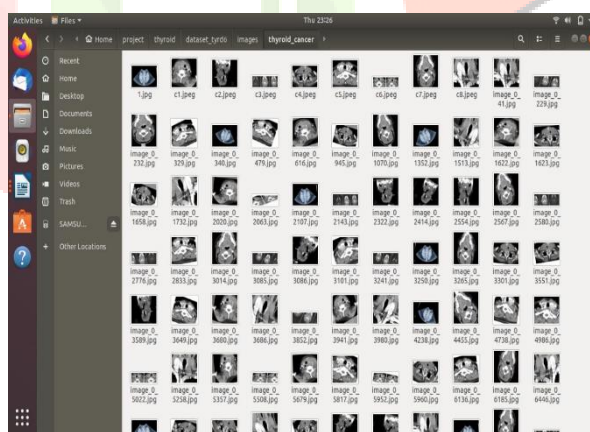


Figure 6.1 Dataset Collected

These datasets are then preprocessed to form an equal aspect ratio so that it can be made ready for training with the model.

The datasets are separated into different categories to undergo preprocessing which can be seen in the below figure



Figure 6.2 Dataset separation

After this the final implementation is done where the training process takes place and the results are obtained.

In order to run the code, first we need to go inside the project folder and select the location to run from there such that the location of the code is the main thing to be considered. This can be seen in the following figure below

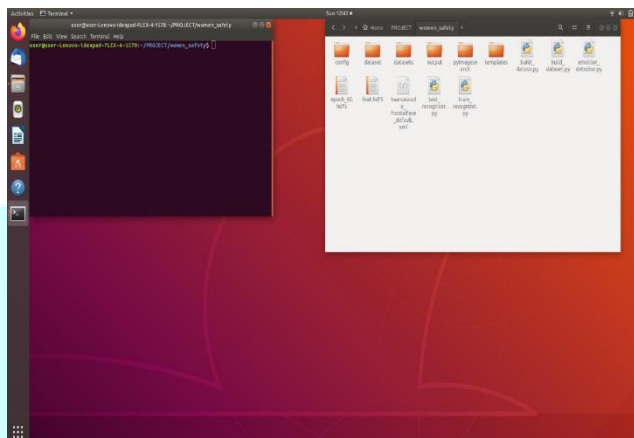


Figure 6.3 Moving Inside the Coding Folder For Execution

Then as the code is run, the execution begins where the datasets are trained using the ResNet architecture and the achieved an accuracy of about 99% and is been printed that can be seen in the following figure

```

Epoch 14/20
151/151 [=====] - 5s 32ms/sample - loss: 0.5598 - acc: 0.9868
15/15 [=====] - 109s 7s/step - loss: 0.6467 - acc: 0.9448 - val_loss: 0.5615 - val_acc: 0.9868
Epoch 15/20
151/151 [=====] - 5s 34ms/sample - loss: 0.5600 - acc: 0.9868
15/15 [=====] - 107s 7s/step - loss: 0.7082 - acc: 0.9294 - val_loss: 0.5618 - val_acc: 0.9868
Epoch 16/20
151/151 [=====] - 5s 31ms/sample - loss: 0.5531 - acc: 0.9868
15/15 [=====] - 107s 7s/step - loss: 0.6644 - acc: 0.9647 - val_loss: 0.5543 - val_acc: 0.9868
Epoch 17/20
151/151 [=====] - 5s 34ms/sample - loss: 0.5543 - acc: 0.9868
15/15 [=====] - 107s 7s/step - loss: 0.6190 - acc: 0.9647 - val_loss: 0.5557 - val_acc: 0.9868
Epoch 18/20
151/151 [=====] - 5s 32ms/sample - loss: 0.5486 - acc: 0.9934
15/15 [=====] - 107s 7s/step - loss: 0.6464 - acc: 0.9536 - val_loss: 0.5489 - val_acc: 0.9934
Epoch 19/20
151/151 [=====] - 5s 34ms/sample - loss: 0.5604 - acc: 0.9801
15/15 [=====] - 107s 7s/step - loss: 0.6609 - acc: 0.9735 - val_loss: 0.5619 - val_acc: 0.9801
Epoch 20/20
151/151 [=====] - 5s 32ms/sample - loss: 0.5549 - acc: 0.9868
15/15 [=====] - 106s 7s/step - loss: 0.6451 - acc: 0.9382 - val_loss: 0.5563 - val_acc: 0.9868
loss
acc
val_loss
val_acc
[INFO] evaluating after fine-tuning...
      precision    recall  f1-score   support

thyroid_cancer    0.96     0.96     0.96         26
thyroid_ditis     0.95     1.00     0.98         21
thyroid_goiter    1.00     1.00     1.00         20
thyroid_hyper     1.00     1.00     1.00         27
thyroid_nodule    1.00     1.00     1.00         34
thyroid_normal    1.00     0.96     0.98         23

 avg / total       0.99     0.99     0.99        151

[INFO] serializing model...

```

Figure 6.4 Efficiency of Model Obtained

The graph plotted for the number of epochs run can be seen in the following figure



Figure 6.5 Graph Plot After the Training Process

Then the recognize code is written which is used to predict the presence of thyroid diseases by importing the model generated after the training process. This can be seen in the following figures

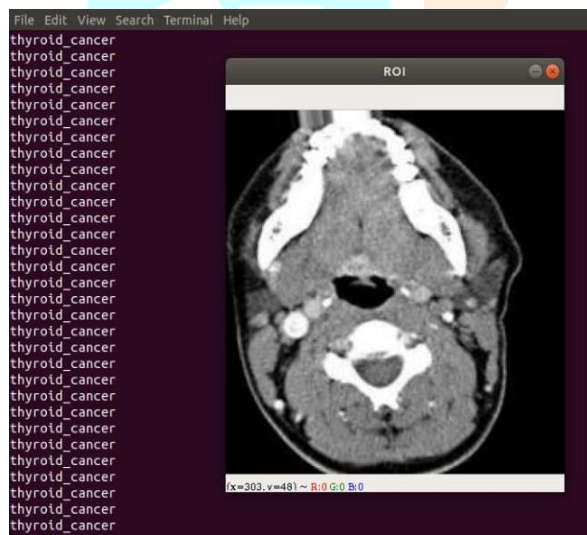


Figure 6.6 Thyroid Cancer Prediction



Figure 6.7 Thyroiditis Prediction

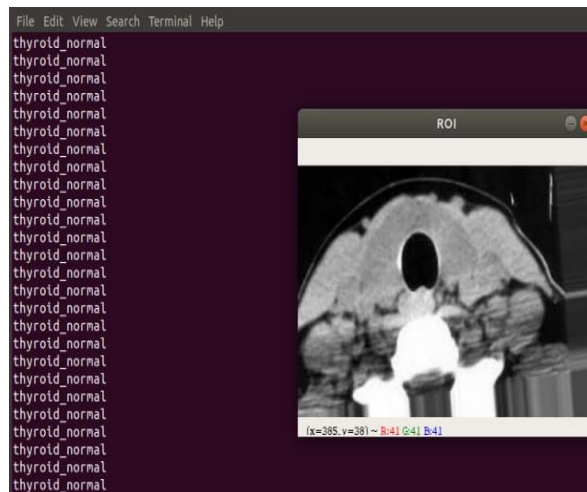


Figure 6.8 Normal Thyroid Prediction

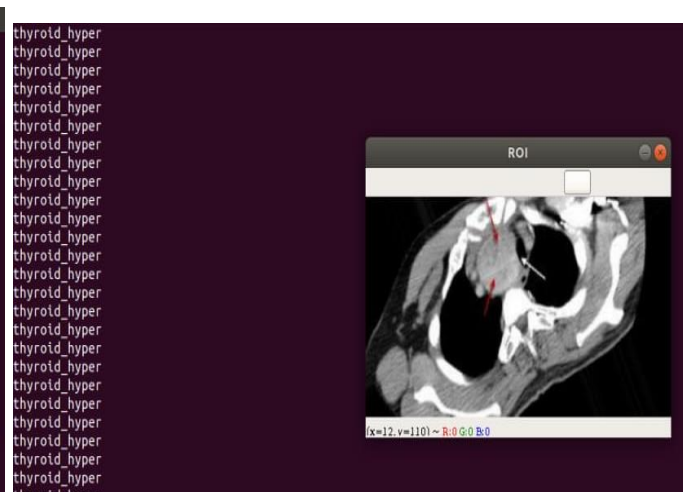


Figure 6.9 Hyperthyroid Prediction

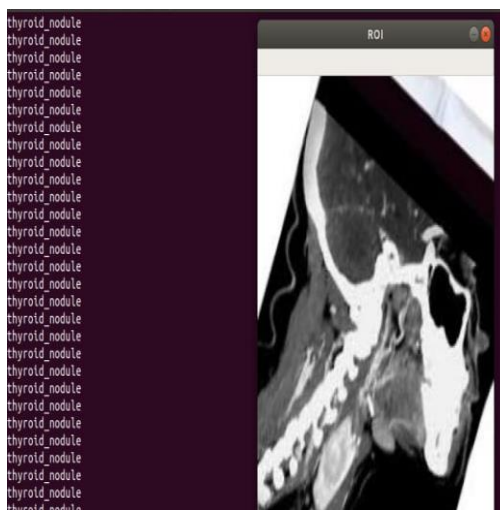


Figure 6.10 Thyroid Nodule Prediction

Figure 6.11 Goitre Prediction

Thus, we have successfully implemented the scope of the project.

VII.CONCLUSION

This project is used to find the presence of thyroid diseases and provide prior measures to avoid the disease, using a web application developed using reactJS. This also help in providing efficient treatment in a most cheap way and eventually reduce the time required for finding the thyroid diseases in the current state. it is done manually which consumes more time and also involves human error rate. So, reduces the time required for manual classification and eliminates the human error rate by this project.

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