

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. Both researchers and doctors are facing the challenges of fighting with thyroid diseases. In that thyroid disease is a major cause of formation in medical diagnosis and in the prediction, onset to which it is a difficult 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. Hyperthyroidism and hypothyroidism are one of the two common diseases of the thyroid that releases thyroid hormones in regulating the rate of body's metabolism. Early detection of thyroid diseases is the top priority for saving the lives of many. 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 paper we develop and apply a novel deep learning architecture to effectively detect and identify the presence of different thyroid diseases such as Hyperthyroidism, Hypothyroidism, Thyroid cancer, Thyroid nodules. This leads to earlier prediction of the presence of the disease and allows us to take prior actions immediately to avoid further consequences in an effective and cheap manner avoiding human error rate. A web application 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.

Keywords: Deep Learning, Thyroid Disease, Hyperthyroidism, Thyroid cancer

1. INTRODUCTION

Hypothyroidism

Hypothyroidism is also referred to as underactive thyroid. In this situation, your thyroid doesn't make enough of the 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.

Thyroiditis

Thyroiditis is essentially 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. Hashimoto's is more common in women, Baker says, and it tends to be inherited. Having another autoimmune disease can also increase your chances of developing Hashimoto's. Within the first year after childbirth, some women may develop postpartum thyroiditis that lasts anywhere from a few weeks up to a few months. The inflammation can cause a period of hyperthyroidism followed by period of hypothyroidism, or for some, just one or the other. For most women, the condition is transient, Baker explains, clearing up in a year or so. "But sometimes it can be permanent." The exact cause isn't clear, but according to the Mayo Clinic, it is believed that women who develop postpartum thyroiditis actually have an underlying autoimmune disorder before pregnancy that flares up after giving birth. Having a viral or bacterial infection can also cause antibodies to attack the thyroid, similarly to Hashimoto's. Some medications, like the heart medication amiodarone, can also cause thyroiditis.

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. However, some thyroid nodules can be cancerous. If you notice any lumps or swelling of your thyroid, you should always get it checked out to rule out cancer.

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 RELATED WORKS

Hui Zhou et al [1] 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 mEcombined 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. The diagnostic accuracy was also compared with VGG-16 based transfer learning model and different input images based model. Analysis of receiver operating characteristic (ROC) curves were performed to calculate optimal area under it (AUC) for benign and malignant nodules. Results: AUC, sensitivity and specificity of OTL were 0.98 (95% confidence interval [CI]: 0.97-0.99), 98.7% (95% confidence interval [CI]: 97.8%-99.6%) and 98.8% (95% confidence interval [CI]: 97.9%- 99.7%) in the final online learning step, which was significantly better than other deep learning models ($P < 0.01$). OTL achieved the most accurate differential diagnosis of benign and malignant thyroid nodules comparing with transfer learning and multi-ROI based model.

Beaumont, P. Onoma et al [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. The obtained efficiency curves are consistent and show that the relative difference in efficiency between the adult and the children case are energy dependent. The developed thyroid phantoms enabled to obtain age specific calibration factors for emergency in vivo monitoring of children. Taking into account the size of thyroid for uptake measurement might be also useful in nuclear medicine department. Indeed, the treatment of benign thyroid disease, like Grave's disease, requires a personalized dosimetry and hence personalized thyroid retention function.

Yi Wang, Na Wang et al [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. Principal component analysis (PCA) was used for feature extraction and reduced the dimension of high- dimension spectral data; then, SVM was employed to establish an effective discriminant model. To improve the efficiency and accuracy of the SVM discriminant model, we proposed artificial fish coupled with uniform design (AFUD) algorithm to optimize the SVM parameters. 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. The experimental results showed that the profile and peak intensities of the serum spectra were very similar between the two groups, while the subtle differences imply that it was possible to preliminarily screen thyroid

function patients through a powerful data analysis algorithm.

Jose M. Anton-Rodriguez et al[4] uses 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 [18F] fluorodeoxyglucose (FDG) and [18F] fluorothymidine (FLT) on separate occasions and scanned for three consecutive 30 min periods moving between scanners. The HRRT images, although noisier, resulted in higher contrast recovery for the smallest cylindrical inserts in comparison to TrueV with and without RM. With the TrueV, higheruptake values were observed in VS lesions with both FDG and FLT which is consistent with greater spill-in from the brain for FDG and bone marrow for FLT. RM decreased measured FDG uptake. For large homogenous lesions the conventional TrueV gives similar or better results compared to the HRRT. For smaller lesions, the HRRT has benefit, with RM on the TrueV unable to restore parity, and with the potential for image artifacts.

Shekoofeh Azizi et al[5]uses a Temporal Enhanced Ultrasound (TeUS), comprising the analysis of variations in backscattered signals from a tissue over a sequence of ultrasound frames, has beenpreviously proposed as a new paradigm for tissue characterization. In this manuscript, wepropose to use deep Recurrent Neural Networks (RNN) to explicitly model the temporal information in TeUS. By investigating several RNN models, we demonstrate that Long Short-Term Memory (LSTM) networks achieve the highest accuracy in separating cancer from benign tissue in the prostate. We also present algorithms for in-depth analysis of LSTM networks. Our in vivo study includes data from 255 prostate biopsy cores of 157 patients. We achieve area under the curve, sensitivity, specificity, and accuracy of 0.96, 0.76, 0.98 and 0.93, respectively. Our result suggests that temporal modeling of TeUS using RNN can significantly improve cancer detection accuracy over previously presentedworks.

III.PROPOSED ARCHITECTURE

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. Both researchers and doctors are facing the challenges of fighting with thyroid diseases. 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. Hyperthyroidism and hypothyroidism are one of the two common diseases of the thyroid that releases thyroid hormones in regulating the rate of body’s metabolism. Early detection of thyroid diseases is the top priority for saving the lives of many. 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 work fig[1] 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 and to check for normal thyroid without the need of several consultations from different doctors. This leads to earlier prediction of the presence of the disease and allows us to take prior actions immediately to avoid further consequences in an effective and cheap manner avoiding human error rate. A web application 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.

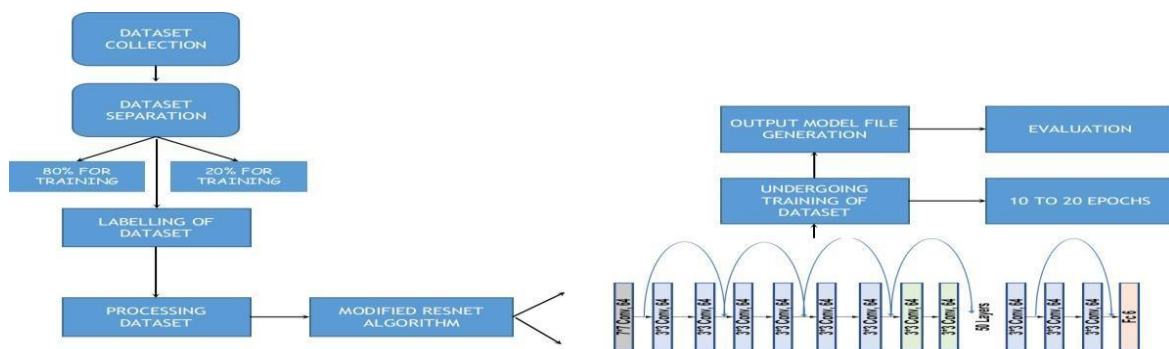


Fig 1. Architecture diagram

IV MODULE DESCRIPTION

In this work, we are going to determine presence of thyroid diseases. By this, 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.

A data set is a collection of data. Deep Learning has become the go-to method for solving many challenging real-world problems. It's definitely by far the best performing method for computer vision tasks. The image above showcases the power of deep learning for computer vision. With enough training, a deep network can segment and identify the "key points" of every person in the image. These deep learning machines that have been working so well need fuel lots of fuel; that fuel is data. The more labelled data available, the better our model performs. The idea of more data leading to better performance has even been explored at a large-scale by Google with a dataset of 300 Million images! When deploying a Deep Learning model in a real-world application, data must be constantly fed to continue improving its performance. And, in the deep learning era, data is very well arguably the most valuable resource. There are three steps of collecting data

Scraping From the Web

Manually finding and downloading images takes a long time simply due to the amount of human work involved. The task probably has some kind of common objects are to be detected. And so that becomes the keyword for web-scraping. It also becomes the class name for that object. From the sounds of it this is of course very easy for a task such as image classification where the images annotations are quite coarse. But to do something like instance segmentation. Every single pixel in the image is required. To get those, it's best to use some really great image annotation tools that are already out there. The paper shows how to create a model that, given a rough set of polygon points around an object, can generate the pixel labels for segmentation. Deep extreme cut is also quite similar except they use only the four extreme points around the object. This will then give some nice bounding box and segmentation labels. Another option is to use an existing image annotation GUIs. Label someone very popular where one can draw both bounding boxes and set polygon points for segmentation maps. Amazon Mechanical Turk is also a cheap option.

Third-party:

Since data has become such a valuable commodity in the deep learning era, many start-ups have started to offer their own image annotation services they'll gather and label the data. Given a description of what kind of data and annotations needed. Mighty is one that has been doing self-driving car image annotation and has become pretty big in the space were at CVPR 2018 too. Payment AI are less specialized than Mighty AI, offering image annotation for any domain. They also offer a couple more tools such as video and landmark annotations.

Pre-processing data module

Deep learning has truly come into the mainstream in the past few years. Deep learning uses neural nets with a lot of hidden layers (dozens in today's state of the art) and requires large amounts of training data. These models have been particularly effective in gaining insight and approaching human-level accuracy in perceptual tasks like vision, speech, language processing. The theory and mathematical foundations were laid several decades ago. Primarily two phenomena have contributed to the rise of deep learning a) Availability of huge data-sets/training examples in multiple domains and b) Advances in raw compute power and the rise of efficient parallel hardware. Building an effective neural network model requires careful consideration of the network architecture as well as the input data format. The most common image data input parameters are the number of images, image height, image width, number of channels, and the number of levels per pixel. Typically, there are 3 channels of data corresponding to the colours Red, Green, Blue (RGB) Pixel levels are usually [0,255]. number of images = 100

- image width, image height =100
- 3 channels, pixel levels in the range [0–255]

Uniform aspect ratio: One of the first steps is to ensure that the images have the same size and aspect ratio. Most of the neural network models assume a square shape input image, which means that each image needs to be checked if it is a square or not, and cropped appropriately. Cropping can be done to select a square part of the image, as shown. While cropping, we usually care about the part in the centre.

V. EXPERIMENTAL WORK



Fig. 2 Dataset Collected

These datasets Fig[2] are preprocessed to from an equal as 4 pect 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 beshown in the Fig[3].



Fig.3 Dataset Preprocessing

Then as the code is run, the execution begins where the datasets are trained using the novel architecture and the achieved an accuracy of about 99% and is been printed that can be seen in the following fig [4]

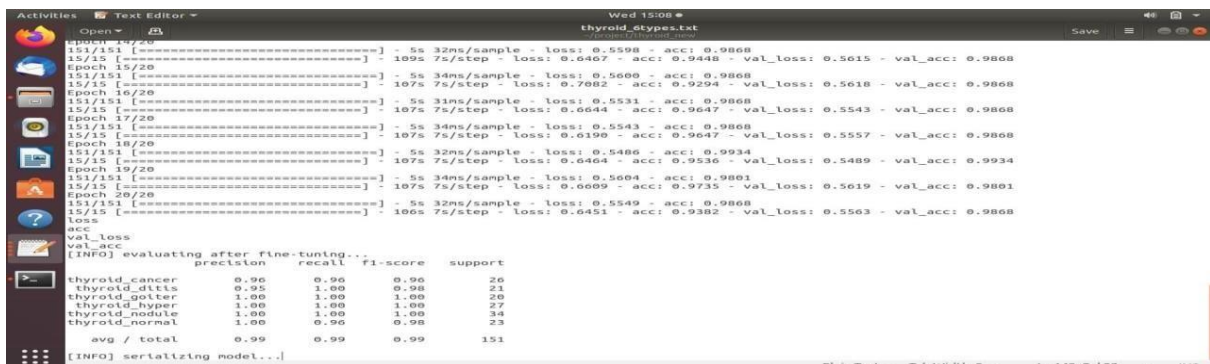


Figure.4. Classification of different Thyroid

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 fig[5][6].



Figure.5. Thyroid Ditis Identified

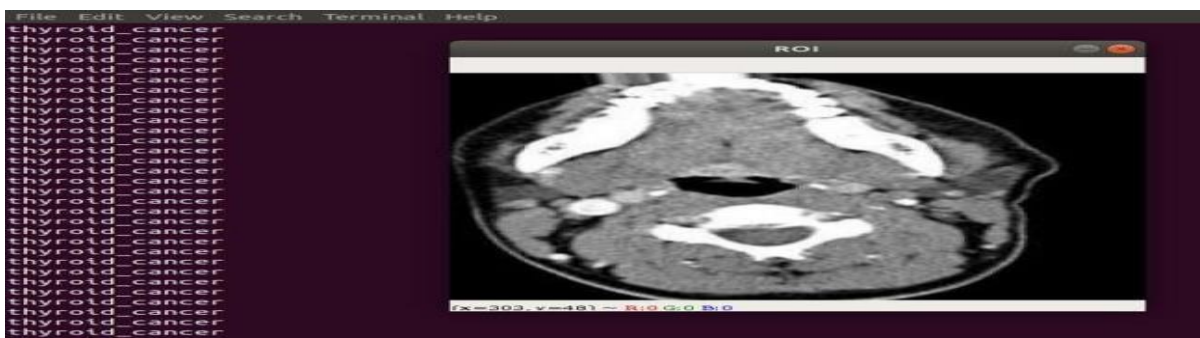


Figure.6. Thyroid Cancer Identified

A web application using reactJS was successfully developed, where the images of the scanned reports are uploaded and the results of the type of disease are displayed to the user.

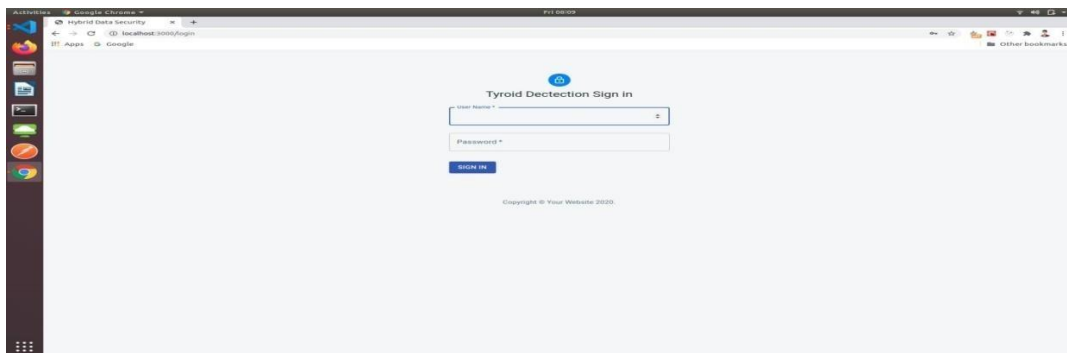


Figure.7 User Login.

The user signs in to his/her account, to perform the diagnosis shown in the fig[7]. Once the user has successfully logged in, the home page is displayed to the user and the user uploads the report in the portal as shown in fig[8]

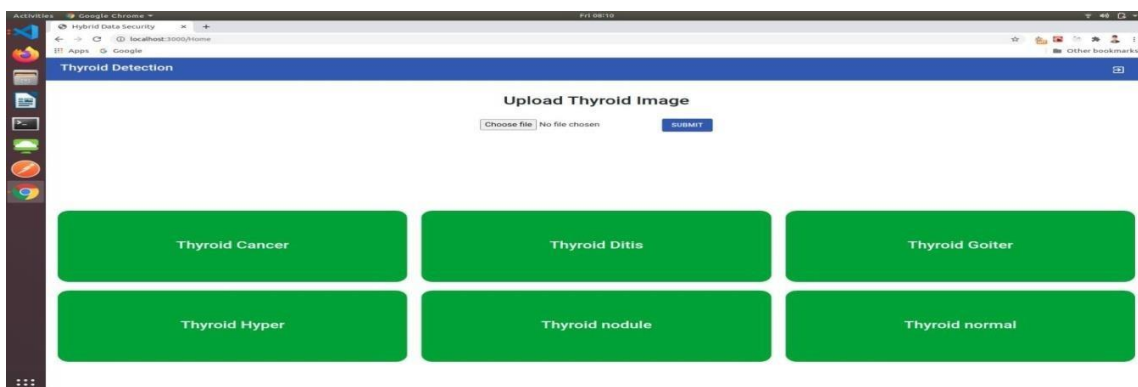


Figure.8. Thyroid Image uploading

The user can then upload the images through the webpage. The user can view the type of thyroid disease the patient is suffering from as shown in the fig[9].

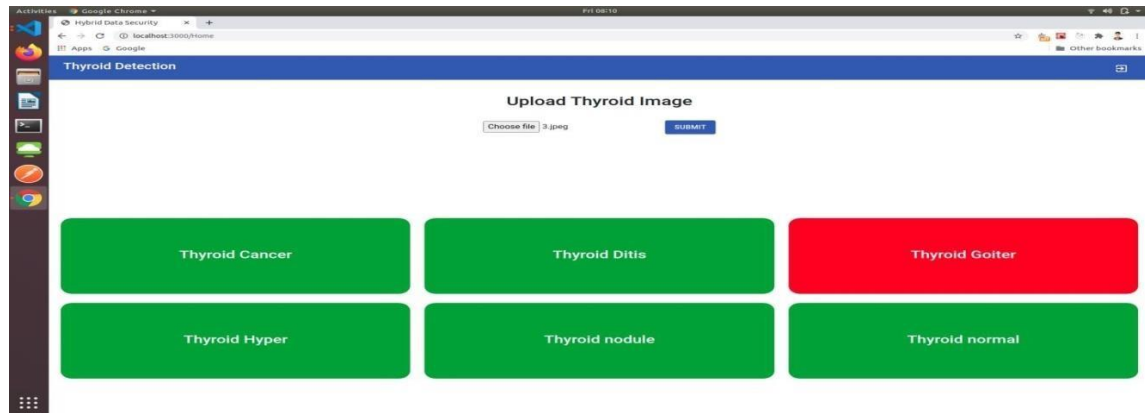


Figure.9.Type of Thyroid disease Identified

VII CONCLUSION

This Work 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 finfing the tyroid 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.

VIII FUTURE ENHANCEMENT

In the coming future, we review the application of the thyroid diseases determine technology in the healthcare field and it can promote for detecting various types of cancer with more accuracy. In medical field they are more chance to develop or convert this project in many ways. Thus, this project has an efficient scope in coming future where manual predicting can be converted to computerized production in a cheap way.

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