

DEVELOPMENT OF WEB APPLICATION TO DETECTING DIFFERENT TYPES OF THYROID DISEASES

Submitted in partial fulfillment of the requirements for the award of

Bachelor of Technology degree in

Biomedical Engineering.

By

MANOJ KUMAR P (37240051)

RANJITH R (37240063)



**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF
BIO AND CHEMICAL ENGINEERING**

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade “A” by NAAC | 12B Status by UGC | Approved by AICTE

JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119

MARCH -2021



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Jeppiaar Nagar, Rajiv Gandhi Salai, Chennai – 600 119

www.sathyabama.ac.in

DEPARTMENT OF BIOMEDICAL ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Manoj Kumar P (37240051), Ranjith R (37240063)** who have done the project work as a team who carried out the project entitled “**Development of Web Application to Detecting Different Types of Thyroid Diseases**” under my supervision from **October 2020 to March 2021**

Dr. T. SUDHAKAR, M.Sc., Ph.D.,

Internal Guide

Dr. T. SUDHAKAR, M.Sc., Ph.D.,

Head of the Department

Submitted for Viva voce Examination held on _____

Internal Examiner

External Examiner

DECLARATION

We, **Manoj Kumar P (37240051)** and **Ranjith R (37240063)** hereby declare that the Project Report entitled “**Development of Web Application to Detecting Different Types of Thyroid Diseases**” done by us under the guidance of **Dr.T.Sudhakar**, Department of Biomedical Engineering is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

DATE:

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1.



2.



SIGNATURE OF THE CANDIDATES

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ABSTRACT

Thyroid is arguably one among the foremost important parts of your body. As a part of the system, this small gland in your neck secretes internal secretion, which is chargeable for directing all of your metabolic functions—that means controlling everything from digestion to mood to energy. When your thyroid is malfunctioning, it can have an effect on any aspect of your health. Both researchers and doctors face the challenges of fighting with thyroid diseases. therein thyroid disease may be a major explanation for formation in diagnosing and within the prediction, onset to which it's a difficult axiom within the medical research. endocrine gland is one in all the foremost important organs in our body. The secretions of thyroid hormones are culpable of controlling the metabolism. Hyperthyroidism and hypothyroidism are one among the 2 common diseases of the thyroid that releases thyroid hormones in regulating the speed of body's metabolism. Early detection of thyroid diseases is that the top priority for saving the lives of the many. Typically, visual examination and manual techniques are used for these styles of a thyroid disease's diagnosis. This manual interpretation of medical images demands time consumption and is very vulnerable to mistakes. Thus, during this project we apply deep learning algorithms to detect the thyroid diseases and its presence without the requirement of several consultations from different doctors. This ends up in earlier prediction of the presence of the disease and allows us to require prior actions immediately to avoid further consequences in an efficient and cheap manner avoiding human error rate.

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LIST OF SYMBOLS AND ABBREVIATIONS

CNN	Convolutional Neural Network
RNNS	Recurrent Neural Network
ILSVRC	ImageNet Large Scale Visual Recognition Challenge
ReLU	Rectified Linear Unit
SARSA	State-Action-Reward-State-Action
DDPG	Deep Deterministic Policy Gradient

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

These are all the foremost common thyroid disorders and what we all know (and don't know) about the causes of every. If you're thinking that you'll have one in all the conditions below, voice your concerns to your doctor so you'll be able to be appropriately screened and obtain your condition in check

Hypothyroidism

Hypothyroidism is additionally observed as underactive thyroid. during this situation, your thyroid doesn't make enough of the hormone, therefore, all of your body's important processes get stalled. Hypothyroidism causes weight gain, reduced appetite, exhaustion, dry skin, and heavy periods, as the body's cells are unable to function at their normal level of performance.

The most common reason for an underactive thyroid is thyroiditis, swelling of the endocrine gland (see below), per the National Institutes of Health.

Thyroiditis

thyroiditis is basically thyroid inflammation. Thyroiditis can cause pain within the thyroid, or lead it to supply an excessive amount of or deficient internal secretion. Some may start to develop symptoms over time, after the inflammation has been impacting the thyroid for ages. the foremost common reason behind thyroiditis is an autoimmune disorder, which causes the system to mistakenly send antibodies to attack the endocrine. the particular one most often related to thyroiditis (and that then causes hypothyroidism) is named Hashimoto's disease. Hashimoto's is more common in women, according to Baker, and it is usually inherited. Having another autoimmune disorder may increase your chances of developing Hashimoto's. Within the primary year after childbirth, some women

may develop postpartum thyroiditis that lasts anywhere from some weeks up to some months. The inflammation can cause a period of hyperthyroidism followed by period of hypothyroidism, or for a few, only 1 or the opposite. for many women, the condition is transient, Baker explains, clearing up in a very year just about. "However, it may be lifelong in some cases. The exact cause is unknown, but according to the Mayo Clinic, women who experience postpartum thyroiditis are likely to have an underlying thyroid condition. Having a viral or bacterial infection also can cause antibodies to attack the thyroid, similarly to Hashimoto's. Some medications, just like the heart medication amiodarone, can even cause thyroiditis.

Hyperthyroidism

When the thyroid is overactive and releases too many hormones, you have hyperthyroidism. Hyperthyroidism is characterised by weight loss, increased appetite, diarrhoea, anxiety, and a fast heartbeat. With all of these phantoms, Beaumon, P., *et al.*, (2019) calculated the counting efficiency for thyroid in vivo monitoring of ^{131}I . The most common reason for hyperthyroidism is an autoimmune disorder called Graves disease, where the body attacks the thyroid and causes it to overproduce thyroid hormones. Postpartum thyroiditis may also cause hyperthyroidism, as can thyroiditis caused by an infection within the body.

Thyroid nodules

A nodule is just an abnormal growth of cells, which may be either solid or fluid-filled. Thyroid nodules are quite common. He goes on to say that the majority of them are mild and present with no symptoms. At the moment, Chunyu Wang, *et al.*, (2020) models for cancer survival prediction have been proposed, but the majority of them only generate prediction models using single genomic or clinical data. The sole way you'll know you've got it's if you notice a lump in your neck or it gets picked up during a routine health exam or scan. Sometimes nodules can cause the thyroid to become overactive, but "in the bulk of cases, they don't seem to be associated with under- or overactive thyroid," Baker says. However, some thyroid nodules is cancerous. If you notice any lumps or swelling of your thyroid, you must always comprehend tested to rule out cancer.

Goiter

Goiter is just a catch-all name for an enlarged thyroid, Baker says. The thyroid will swell in both hyperthyroidism and hypothyroidism. The results of a large, prospective, blinded study validating the ESS algorithm in patients with thyroid nodules were published by Jennifer E, *et al.* in 2016. Several nodules clumped together may also cause a goiter, as can thyroiditis, thyroid cancer, and even hormonal fluctuations during pregnancy. Goiters may form if you have got an iodine deficiency, but this is not a controversy that we actually see any longer within the U.S. A goiter that won't large enough to impact swallowing or breathing is nothing to fret about, but knowing what caused it to make is vital to urge to the underside of the other thyroid problems you've got.

Thyroid cancer

According to the National Cancer Institute, there have been an estimated 62,450 new cases of thyroid cancer in 2014. the speed has been increasing in recent years, which experts estimate is partly because new technologies have made it easier to detect. the complete reason for this increase, though, isn't yet known. Hui Zhou, Hui Zhou, Hui Zhou, Hui Zhou, Hui Zhou (2020) The diagnostic accuracy was also compared to a transfer learning model based on VGG-16 and a model based on different input images. the nice news is that thyroid cancer is typically very treatable, and also the survival rates are high. Jose M,*et al.*,(2019) A modified Esser phantom and 6 neurofibromatosis 2 (NF2) patients with vestibular schwannomas (VS) were scanned using both scanners. Thyroid cancer often presents without symptoms and just causes a goiter or nodules that typically won't impact the thyroid's function or cause any pain within the early stages. because it progresses and cancerous nodules grow, you'll experience pain within the neck, difficulty swallowing, or a hoarse voice.

1.2 TECHNOLOGIES USED:

1.2.1 Deep learning

Deep learning is also a form of computer software that simulates a brain's network of neurons. It is a branch of machine learning, and it is known as deep learning because it employs deep neural networks. • The Input Layer is the first layer; the Output Layer is the last layer; and all layers in between are known as Hidden Layers. The term "deep" refers to the network's ability to connect neurons in new ways.

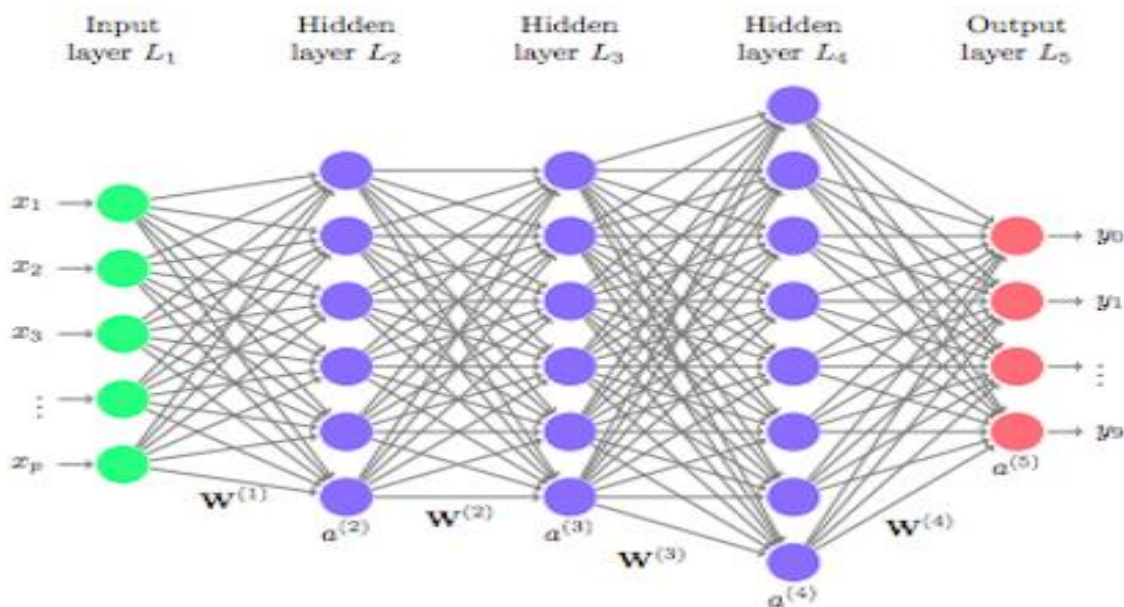


Figure 1.1 Deep Learning Layers

Each Hidden layer consists of neurons. The neurons are connected to every other. The neuron will process so propagate the sign it receives the layer above it. The strength of the signal given the neuron within the next layer depends on the load, bias and activation

function. The network collects large volumes of computer files and processes them across several layers, with each layer allowing the network to learn increasingly complex features of the data. Amir Mirbeik-Sabzevari, *et al.* (2018) present new skin-equivalent semisolid phantoms that are stable and broadband for simulating millimetre wave interactions with human skin and skin tumours. Deep learning could be a powerful tool to form prediction an actionable resultPattern discovery (unsupervised learning) and knowledge-based prediction are two areas where deep learning excels. Big data is that the fuel for deep learning. Julien Rouyer and friends (2018) As previously demonstrated in ex vivo mouse cancer models, spectral-based quantitative ultrasound (QUS) characterizations can give better diagnostic management. When both are combined, a company can reap unprecedented ends up in term of productivity, sales, management, and innovation. Deep learning can outperform traditional method. Deep learning algorithms, for example, are 41% more accurate in image classification than machine learning algorithms, 27% more accurate in face recognition, and 25% more accurate in voice recognition.

1.2.1.1 Deep Learning Process

A deep neural network provides state-of-the-art accuracy in many tasks, from object detection to speech recognition. They can learn automatically, without predefined knowledge explicitly coded by the programmers.

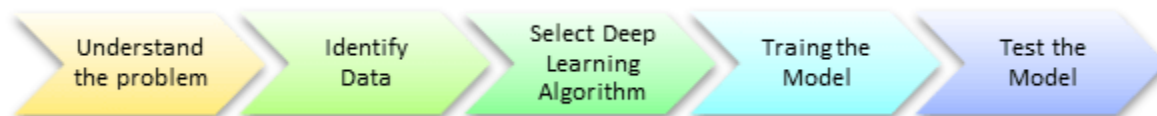


Figure 1.2 Deep Learning Process

To grasp the thought of deep learning, imagine a family, with an infant and fogeys. The toddler points objects together with his finger and always says the word 'cat.' As its parents are concerned about his education, they keep telling him 'Yes, that's a cat' or 'No,

that's not a cat. The infant continues to point to things, but with cats, he becomes more precise.. the small kid, deep down, doesn't know why he can say it's a cat or not. He has just learned a way to hierarchy complex features bobbing up with a cat by observing the pet overall and still specialize in details like the tails or the nose before to form up his mind. A neural network works quite the identical. Each layer represents a deeper level of data, i.e., the hierarchy of information. A neural network with four layers will learn more complex feature than therewith with two layers. Koyel Mandal and colleagues (2018) The gold standard for thyroid cancer diagnosis is fine-needle aspiration (FNA). The learning occurs in two phases. • The first phase consists of applying a nonlinear transformation of the input and make a statistical model as output. • The second phase aims at improving the model with a mathematical method referred to as derivative. The neural network repeats these two steps hundreds to thousands of times before it achieves a degree of accuracy that is appropriate. The repeat of this two-phase is named an iteration.

1.2.1.2 Classification of Neural Networks

Shallow neural network: The Shallow neural network has only one hidden layer between the input and output.

Deep neural network: Deep neural networks have more than one layer. For instance, Google LeNet model for image recognition counts 22 layers.

Nowadays, deep learning is used in many ways like a driverless car, mobile phone, Google Search Engine, Fraud detection, TV, and so on.

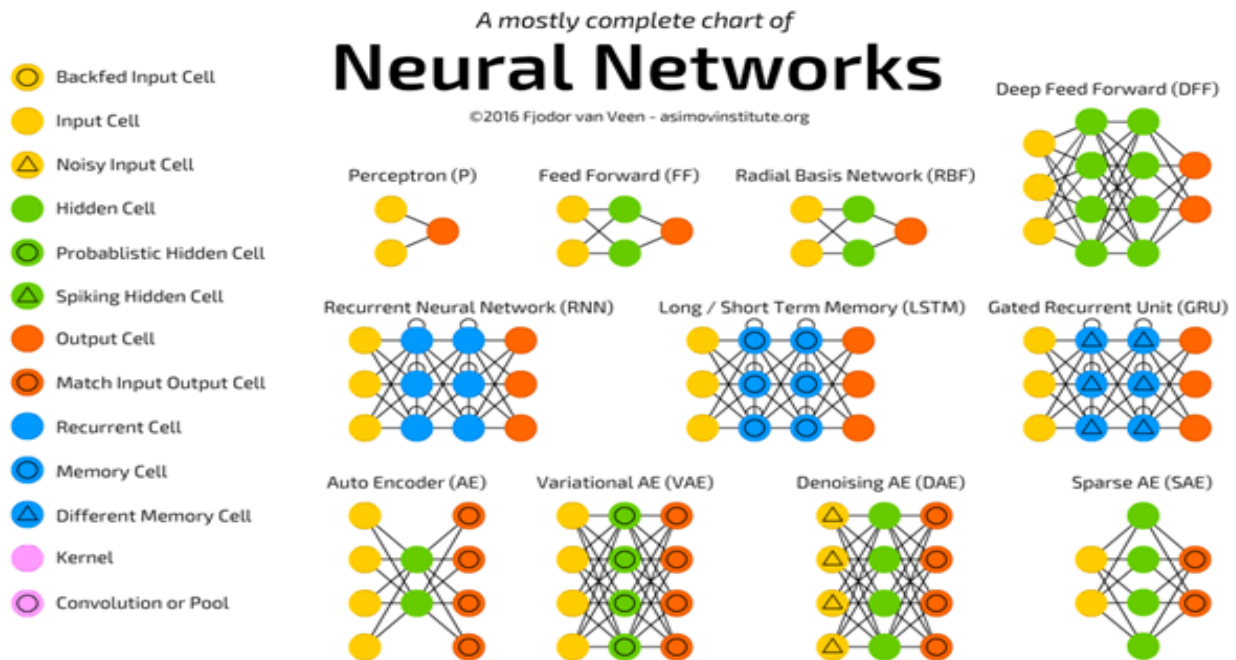


Figure 1.3 Types of Deep Learning Networks

1.2.1.3 Feed-Forward Neural Networks

The simplest form of artificial neural network. With this kind of architecture, information flows in mere one direction, forward. It means that data flows from the input layer to the "hidden" layers and finally to the output layer. The network doesn't have a loop. Information stops at the output layers.

1.2.1.4 Recurrent neural networks (RNNs)

RNN could be a multi-layered neural network which will learn data sequences and produce variety or another sequence by storing information in background nodes. RNNs are compatible for processing sequences of inputs. The process of RNNs are explained below:

- The RNN neurons will receive a proof that time to the beginning of the sentence.
- The network receives the word "Do" as an input and produces a vector of the quantity. This vector is fed back to the neuron to supply a memory to the network. This stage aids the network in remembering that it obtained "Do" within the first place, which it'll move to the subsequent words within the same manner.
- The end occurs after receiving the word

"a." The neural network will provide a probability for every English word that may be wont to complete the sentence. A well-trained RNN probably assigns a high probability

Common uses of RNN

- Help securities traders to return up with analytic reports
- Detect abnormalities within the contract of monetary statement
- Detect fraudulent credit-card transaction
- Provide a caption for images
- Power chatbots
- When practitioners are dealing with time-series data or sequences, RNN is commonly used.

1.2.1.5 Convolutional Neural Networks (CNN)

CNN is a multi-layered neural network with a unique architecture designed to extract increasingly complex features of the data at each layer to determine the output. CNN's are well suited for perceptual tasks

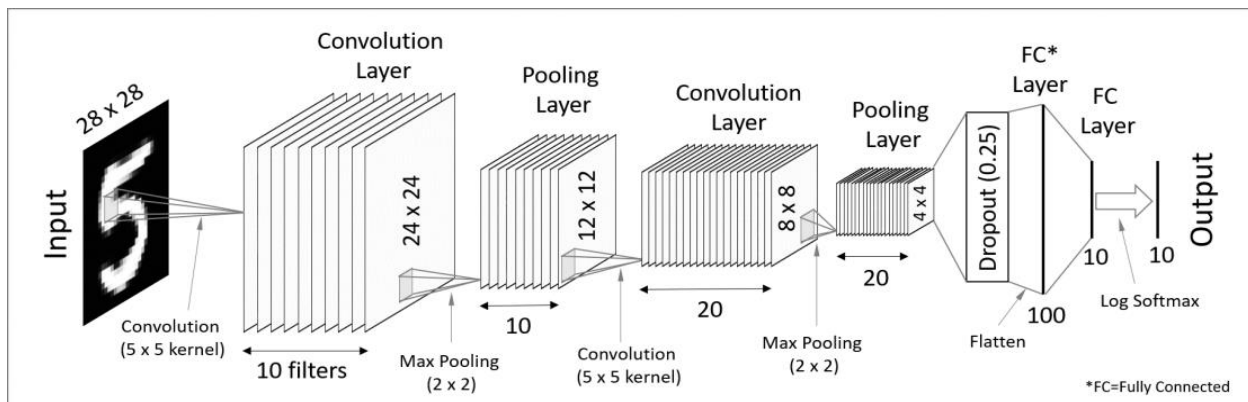


Figure 1.4 CNN

CNN is generally used when there's an unstructured data set (e.g., images) and also the practitioners must extract information from it

For instance, if the task is to predict a picture caption:

- The CNN receives a picture of to illustrate a cat, this image, in computer term, could be a collection of the pixel. Generally, one layer for the greyscale picture and three layers for a color picture.
- During the feature learning (i.e., hidden layers), the network will identify unique features, as an example, the tail of the cat, the ear, etc.
- When the network thoroughly learned the way to recognize an image, it can provide a probability for every image it knows. The label with the best probability will become the prediction of the network.

A Convolutional Neural Network (CNN, or ConvNet) are a special reasonably multi-layer neural networks, designed to acknowledge visual patterns directly from pixel images with minimal Pre-processing. The ImageNet project may be a large visual database designed to be used in visual visual perception software research. The ImageNet project runs an annual software contest, the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), where software programs compete to properly classify and detect objects and scenes.

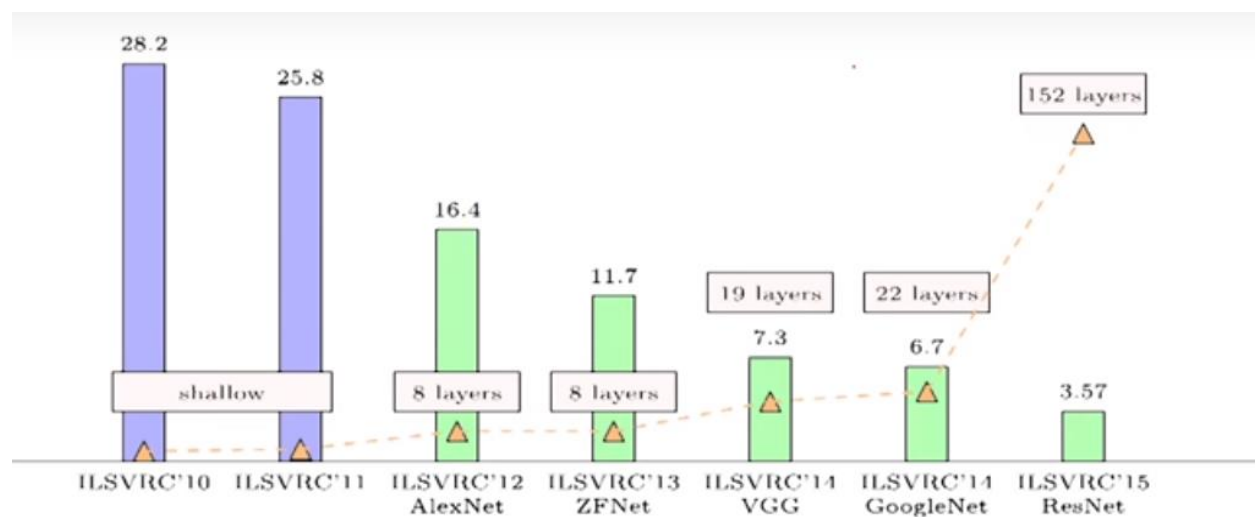


Figure 1.5 Types of CN

CHAPTER - 2

LITERATURE REVIEW

Hui Zhou *et al.*, (2020) proposed Online Transfer Learning for Differential Diagnosis of Benign and Malignant Thyroid Nodules with Ultrasound Images. 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. 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.

Beaumont *et al.*, (2019) proposed Age-specific experimental and computational calibration of thyroid in vivo monitoring. Age-specific thyroid phantoms like 5, 10, 15 years-old and also the adult case is designed and made with a 3D printer. Reference measurements of the counting efficiency are administered for thyroid in vivo monitoring of ^{131}I with of these phantoms. These measurements were taken for IRSN's emergency mobile devices. the complete efficiency curve, between 29 and 1000 keV, was then obtained by Monte-Carlo calculations and validated by comparison of an outsized set of measurements. The obtained efficiency curves are consistent and show that the relative difference in efficiency between the adult and also the children case is energy dependent. The developed thyroid phantoms enabled to get age specific calibration factors for emergency in vivo monitoring of youngsters. Taking into consideration the scale of thyroid for uptake measurement could be also useful in medicine department. Indeed, the treatment of benign thyroid disease, like Grave's disease, requires a personalised dosimetry and hence personalized thyroid retention function.

Yi Wang *et al.*, (2019) proposed Deeply-Supervised Networks with Threshold Loss for Cancer Detection on Automated Breast Ultrasound. Using serum Raman spectroscopy and a support vector machine, this study presents a fast and low-cost method for detecting thyroid dysfunction (SVM). The serum samples taken from 34 thyroid dysfunction patients and 40 healthy volunteers were measured during this study. The Raman bands within the calculated serum spectra were tentatively assigned, implying specific biomolecular differences 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 ascertain an efficient discriminant model. to enhance the efficiency and accuracy of the SVM discriminant model, we proposed artificial fish not to mention uniform design (AFUD) algorithm to optimize the SVM parameters. the typical accuracy of 30 discriminant results reached 82.74%, and also 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 2 groups, while the subtle differences imply that it hadziid has been possible to preliminarily screen thyroid function patients using a strong data analysis algorithm.

Jose M *et al.*, (2019) proposed Comparison of a Standard Resolution PET-CT Scanner with an HRRT Brain Scanner for Imaging Small Tumors Within the Head. We compared a traditional PET-CT scanner (Siemens Biograph True Point True) with and without resolution modelling (RM) image reconstruction with a high-resolution research tomograph (HRRT) so as to assess the utility of conventional scanners for brain scanning. Both scanners were used to scan a modified Asser phantom and six neurofibromatosis 2 (NF2) patients with vestibular schwannomas (VS). On two separate occasions, the phantom was filled with fluorine-18 (40 MBq, 4:1 contrast ratio) and scanned for 60 minutes. Patients were issued 200 MBq of [18F] on three different occasions. fluorodeoxyglucose (FDG) and [18F] fluor thymidine (FLT) and scanned for three consecutive 30-minute cycles, switching between scanners. Compared to True with and without RM, HRRT photos had better contrast recovery for the tiniest cylindrical inserts, despite being noisier.

Purang Abomasum, *et al.*, (2018) proposed Prostate Cancer Detection Analysis for Temporal Enhanced Ultrasound IEEE Transactions on Medical Imaging. The study of differences in backscattered signals from a tissue over a series of ultrasound frames, known as Temporal Enhanced Ultrasound (TeUS), has previously been proposed as a novel paradigm for tissue characterization. We suggest using deep Recurrent Neural Networks (RNN) to directly model the temporal information in TeUS in this paper. By investigating several RNN models, we demonstrate that Long memory (LSTM) networks achieve the most effective accuracy in separating cancer from benign tissue within the prostate. Algorithms for in-depth study of LSTM networks are also presented. Data from 255 prostate biopsy cores from 157 patients were used in our in vivo analysis. We achieve 0.96, 0.76, 0.98, and 0.93 for area under the curve, sensitivity, precision, and accuracy, respectively. Our findings indicate that using RNN to model TeUS temporal data will dramatically increase cancer detection accuracy over previous methods. works.

Koyel Mandal *et al.*, (2018) proposed Biomarker Identification for Cancer Disease Using Biclustering Approach: An Empirical Study. In clinical practice, an amazing majority of biopsied thyroid nodules are benign. Therefore, there's a desire for a complementary and non-invasive imaging tool to supply clinically relevant diagnostic information about thyroid nodules to scale back the speed of unnecessary biopsies. The aim of this study was to see whether comb-push ultrasound shear elastography (CUSE) could be used to determine the mechanical properties (i.e., stiffness) of thyroid nodules. This information to assist classify nodules as benign or malignant. CUSE could be a fast and robust 2-D shear elastography technique within which multiple laterally distributed acoustic radiation force beams are utilized simultaneously to provide shear waves. Unlike other shear elasticity imaging modalities, CUSE doesn't suffer from limited field of view (FOV) thanks to shear wave attenuation and might provide an oversized FOV at high frame rates' assess CUSE's usefulness in thyroid imaging Before the study, a group of 5 healthy volunteers and 10 patients with ultrasound-detected thyroid nodules were tested. fine needle aspiration biopsy. Young's modulus (E) was calculated from the measured shear wave speeds in normal thyroid tissue and thyroid nodules, which is a measure of tissue

stiffness. Our results indicate a rise in E for thyroid nodules compared to normal thyroid tissue. This increase was significantly higher than malignant nodules compared to benign.

Julien Rouyer *et al.*, (2015) proposed In vivo Estimation of Attenuation and Backscatter Coefficients for Human Thyroids. Fine-needle aspiration (FNA) remains the gold standard of the diagnosis of thyroid cancer. However, currently an oversized number of FNA biopsies lead to 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 stronger diagnostic management as previously demonstrated in mouse cancer models *ex vivo*. As a primary step towards understanding the potential of QUS markers for thyroid disease management, this paper deals with the spectral-based QUS estimation of healthy human thyroids *in vivo*. Twenty volunteers were inspected by a trained radiologist using two ultrasonic imaging systems, which allowed to amass radiofrequency data spanning the three to 16 MHz frequency range. Estimates of attenuation coefficient slope (ACS) using the spectral logarithmic difference method had a median value of 1.69 dB/(cm.MHz) with a customary deviation of 0.28 dB/(cm.MHz). Estimates of backscatter coefficient (BSC) using the reference phantom method had a median value of 0.18 sr-1.cm-1 over the useful frequency range. Over the study frequency spectrum, the inter-subject variability when estimating BSCs was just 1.5 dB. The effectiveness of three scattering models (fluid sphere, Gaussian, and exponential type factors) was also evaluated when fitting the experimentally estimated BSCs. Quantitative ultrasound characterization of the healthy human thyroid has been presented through the estimation of the ACSs and therefore the BSCs over 20 volunteers inspected in a very clinical context.

Chunyu Wang *et al.*, (2019) proposed A Cancer Survival Prediction Method Based on Graph Convolutional Network. 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. Many calculation models for cancer survival prediction have been proposed at present, but most of them generate prediction models only by using single genomic data or clinical data. Multiple genomic data and clinical data have not been integrated yet to take a comprehensive consideration of cancers and predict their survival. Method: In order to effectively integrate multiple genomic data (including genetic expression, copy number alteration, DNA methylation and exon expression) and clinical data and apply them to predictive studies on cancer survival, similar network fusion algorithm (SNF) was proposed in this paper to integrate multiple genomic data and clinical data so as to generate sample similarity matrix, mi redundancy and max-relevance algorithm (mRMR) was used to conduct feature selection of multiple genomic data and clinical data of cancer samples and generate sample feature matrix, and finally two matrixes were used for semi-supervised training through graph convolutional network (GCN) so as to obtain a cancer survival prediction method integrating multiple genomic data and clinical data based on graph convolutional network (GCGCN).

Wenfeng Song *et al.*, (2017) proposed Multi-task Cascade Convolution Neural Networks for Automatic Thyroid Nodule Detection and Recognition. Thyroid ultrasonography may be a widely-used clinical technique for nodule diagnosis in thyroid regions. However, it remains difficult to detect and recognize the nodules thanks to low contrast, high noise, and diverse appearance of nodules. In today's clinical practice, senior doctors could pinpoint nodules by analyzing global context features, local geometry structure, and intensity changes, which might require rich clinical experience accumulated from hundreds and thousands of nodule case studies. To alleviate doctors' tremendous labor within the diagnosis procedure, we advocate a machine learning approach to the detection and recognition tasks during this paper. specifically, we develop a multi-task cascade convolution neural network framework (MCCNN) to take advantage of the context information of thyroid nodules. it's going to be noted that, our framework is constructed upon an oversized number of clinically-confirmed thyroid ultrasound images with accurate and detailed ground truth labels. Other key advantages of our framework

result from a multi-task cascade architecture, two stages of carefully-designed deep convolution networks so as to detect and recognize thyroid nodules in a very pyramidal fashion, and capturing various intrinsic features in an exceedingly global-to-local way.

Xiangxiang Zheng *et al.*, (2017) proposed Rapid and Low-Cost Detection of Thyroid Dysfunction Using Raman Spectroscopy and an Improved Support Vector Machine. Using serum Raman spectroscopy and a support vector machine, this study presents a fast and low-cost method for detecting thyroid dysfunction (SVM). Serum samples were collected from 34 thyroid dysfunction patients and 40 healthy volunteers for this analysis. The Raman bands in the measured serum spectra were tentatively assigned, implying specific biomolecular differences between the groups. PCA was used to extract features and reduce the dimension of high-dimension spectral data, followed by SVM to create an efficient discriminant model. The artificial fish was suggested by us. Coupled with uniform design (AFUD) algorithm to optimize the SVM parameters in order to increase the efficiency and accuracy of the SVM discriminant model.

Nikhil S. Narayan *et al.*, (2016) proposed Speckle Patch Similarity for Echogenicity based Multi-Organ Segmentation in Ultrasound Images of the Thyroid Gland. When an ultrasound wave is stimulated at the region of interest, US imaging is used to create a brightness image from the enhanced back-scatter echo. As a result of backscattering and subsequent amplification, imaging artefacts and speckles appear in the image. We demonstrate the usefulness of speckle related pixels and imaging artefacts as sources of knowledge to perform multi-organ segmentation in US images of the thyroid. The speckle related pixels are clustered supported a similarity constraint to quantize the image. The quantization results are wont to locate useful anatomical landmarks that aid the detection of multiple organs within the image which are the endocrine, the arteria Carotis, the muscles and also the trachea. The spatial locations of the arteria Carotis and also the trachea are wont to estimate the boundaries of the endocrine in transverse US scans. The SRR's are wont to detect hyper-echoic anatomical landmarks which are accustomed detect and segment other organs using local phase-based methods. The proposed

method outperforms current methods for segmenting both individual and multiple organs, with an overall accuracy of over 92 percent.

Jennifer E *et al.*, (2016) proposed Preoperative Discrimination of Benign from Malignant Disease in Thyroid Nodules with Indeterminate Cytology Using Elastic Light-Scattering Spectroscopy. Thyroid nodules are normal, and fine needle aspiration biopsy (FNAB) is often used to assess the existence of malignancy and to guide treatment. Unfortunately, cytology alone does not distinguish between benign and malignant thyroid nodules in around 15–30% of FNAB-evaluated nodules. These patients need surgery solely for the purpose of diagnosis; the majority of these nodules turn out to be benign in the end. The use of elastic light scattering spectroscopy (ESS), which tests spectral differences between benign and malignant thyroid nodules, has shown promise in determining the benign status of thyroid nodules prior to surgery. Spectra from human thyroid tissue were collected using an ESS method.

Micha Feigin *et al.*, (2016) proposed A Deep Learning Framework for Single-Sided Sound Speed Inversion in Medical Ultrasound. Ultrasound elastography is gaining popularity as a cost-effective and practical diagnostic method for cancer detection and differentiation, as well as thyroid disease diagnosis. Unfortunately, due to high power requirements, state-of-the-art shear wave imaging techniques, which are critical to achieving this goal, are limited to high-end ultrasound hardware; they are also extremely sensitive to noise. Patient and sonographer motion, and usually, suffer from low frame rates. We present an alternative approach using single-sided pressure-wave sound, which is motivated by research and theory showing that longitudinal wave sound speed has diagnostic abilities similar to shear wave imaging. measurements from channel data. Methods: In this paper, we show how to use a fully convolutional deep neural network to solve a single-sided sound speed inversion problem. For training, we use simulations, which allow us to generate an infinite amount of ground truth data. We show that at high frame rates, it is possible to invert for longitudinal sound speed in soft tissue. We validate the strategy on simulated data. On the basis of minimal real-world evidence, we present highly encouraging results. Conclusion: Sound speed inversion on channel data has a lot of

promise, and deep learning technologies make it possible to do it in real time. Significance: Specialized shear wave ultrasound systems remain inaccessible in many locations longitudinal sound speed and deep learning technologies enable an alternate approach to diagnosis supported tissue elasticity. High frame rates are possible.

Amir Mirbeik-Sabzevari *et al.*, (2015) proposed Ultra-Wideband, Stable Normal and Cancer Skin Tissue Phantoms for Milli-meter-Wave Skin Cancer Imaging. This paper presents new skin-equivalent semisolid phantoms that are stable and broadband for simulating millimetre wave interactions with human skin and carcinoma. Realistic skin phantoms function a useful tool for exploring the feasibility of latest technologies are improving design concepts associated with milli-meter-wave carcinoma detection methods. Normal and malignant skin tissues are separately mimicked by using appropriate mixtures of deionized water, oil, gelatine powder, formaldehyde, TX-150 (a gelling agent, widely stated as 'super stuff'), and detergent. The dielectric properties of the phantoms are measured using a slim-form open-ended coaxial probe in combination with a millimeter-wave vector network analyser over the frequency range of 0.5–50 GHz. The measured permittivity results show excellent match with ex-vivo, fresh skin (both normal and malignant) permittivity determined in our prior beat the whole frequency range. This work leads to the closest match among all phantoms reported within the literature to surrogate human skin tissues. the soundness of dielectric properties over time is additionally investigated. The phantoms demonstrateto long-term stability (up to 7 months was investigated). additionally, the penetration depth of milli-meter waves into normal and malignant skin phantoms is calculated. The majority of the epidermis and dermis skin structures are affected by millimetre waves, which penetrate the human skin deep enough (0.6 mm on average at 50 GHz).

Yanbo Wang *et al.*, (2015) proposed A graphical model of smoking-induced global instability in lung cancer. Smoking is that the major reason behind carcinoma and also the leading reason for cancer-related death within the world. the foremost current view about carcinoma isn't any longer limited to individual genes being mutated by any carcinogenic

insults from smoking. Instead, tumorigenesis is a phenotype conferred by a number of systematic and global changes, resulting in significant heterogeneity and variance in both the genotypes and phenotypes of individual cancer cells. Thus, strategically it's foremost important to develop a strategy to capture any consistent and global alterations presumably shared by most of the cancerous cells for a given population. This is often particularly true that nearly all of the information collected from solid cancers (including lung cancers) are usually distant apart over an outsized span of temporal or perhaps spatial contexts. Here we report a multiple non-Gaussian graphical model to reconstruct the gene interaction network using two previously published organic phenomenon datasets. Our graphical model aims to selectively detect gross structural changes at the extent of gene interaction networks. Our approach has been thoroughly validated, demonstrating good robustness, as well as the expected selectivity and specificity, which backed up our biological findings. In summary, gene regulatory networks are still relatively stable during presumably the first stage of neoplastic transformation. However, structural variations between carcinoma and its normal control can be observed, including the benefit of functional modules for cellular proliferations such as EGFR and PDGFRA, as well as the loss of the critical IL6 module, indicating their potential as drug targets. Our system, interestingly, can detect early modular changes, with ALDH3A1 and its associated interactions strongly implicated as a potential early marker, whose activations tend to alter LCN2. module furthermore as its interactions with the important TP53-MDM2 circuitry. Our strategy using the graphical model to reconstruct gene interaction work with biologically-inspired constraints exemplify the importance and sweetness of biology in developing any bio-computational approach.

CHAPTER - 3

AIM AND SCOPE

3.1 AIM

- To determine the presence of thyroid diseases at an early stage.
- To reduce the time required to detect the presence of thyroid diseases.
- To determine the cheap way to predict the thyroid diseases presence.

3.2 SCOPE

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.

3.3 EXISTING SYSTEM:

The aim of this study was to propose an online transfer learning (OTL) model for the diagnosis of benign and malignant thyroid nodules from ultrasound (US) images. The OTL method mixed transfer learning and online learning strategies. The model was developed using two datasets: 1750 thyroid nodules with 1078 benign and 672 malignant nodules, and 3852 thyroid nodules with 3213 benign and 639 malignant nodules. The diagnostic accuracy was also compared to a transfer learning model based on VGG-16 and a model based on different input images. Analysis of receiver operating characteristic (ROC) curves were performed to calculate optimal area thereunder (AUC) for benign and malignant nodules. 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%) within the ultimate online learning step, which was significantly better than other deep learning models ($P < 0.01$). OTL achieved the foremost accurate diagnosing of benign and malignant thyroid nodules comparing with transfer learning and multi-ROI based model.

3.4 DISADVANTAGES OF EXISTING SYSTEM:

- One of the main disadvantages is that the transfer learning only works if the initial and target problems of both models are similar enough. If the new task's first round of training data differs too much from the old task's data, the trained models can perform worse than anticipated.
- Only benign and malignant form of thyroid presence is detected in the existing system.
- Accuracy decreases with decrease in the amount of data

3.5 PROPOSED SYSTEM:

The thyroid gland is arguably one of the most vital organs in your body. Thyroid hormone is produced by this small gland in your neck, which is part of the endocrine system and is responsible for directing all of your metabolic functions, including

digestion, mood, and energy. When your thyroid is malfunctioning, it can have an effect on any aspect of your health. Both researchers and doctors are facing the challenges of fighting with thyroid diseases. Thyroid disorder is a significant cause of formation in medical diagnosis and prediction, and its onset is a challenging axiom in medical science. The thyroid gland is one of our body's most essential organs. Thyroid hormone secretions are responsible for regulating metabolism. Hyperthyroidism and hypothyroidism are two common thyroid diseases in which thyroid hormones are released to regulate the rate of the 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 consumes a lot of time and is vulnerable to errors. Thus, in this project we apply deep learning algorithms to detect the thyroid diseases and its presence 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.

3.6 ADVANTAGES OF PROPOSED SYSTEM:

- An early prediction of thyroid diseases.
- Easy and cheap to determine the presence of thyroid diseases.
- Eliminates the human error rate.
- Saves time and efficient.

3.7 APPLICATIONS:

- Used in hospitals.
- Used in endocrinology test centers.
- Early prediction of thyroid cancers.

CHAPTER: 4

MATERIALS AND METHOD

DETAILED DESIGN OF THE PROJECT:

This chapter describes the overall design. It also describes each module that is to be implemented.

4.1 SYSTEM ARCHITECTURE

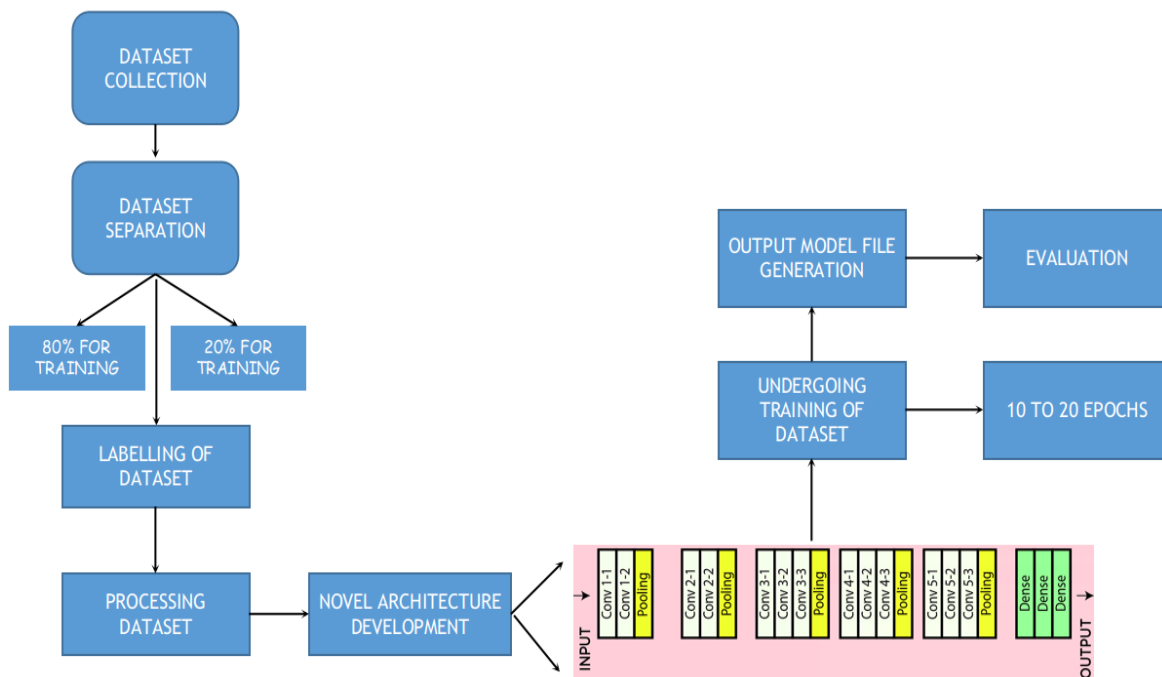


Figure: 4.1: System Architecture

4.2 WORKING

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 VGG16 algorithms. 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. Thus, this method provides an effective and cheap method to determine the presence of thyroid diseases than the methodologies used nowadays

4.3 MODULE DESCRIPTION

- Dataset Collection Module
- Preprocessing Data Module
- Thyroid prediction using the architecture

4.3.1 Data Collection

A data set is a set of information. Deep Learning has emerged as the preferred tool for tackling a wide range of difficult real-world problems. It is, without a doubt, the most effective approach for computer vision tasks. Deep learning's strength in computer vision is demonstrated in the picture above. A deep network can segment and classify the "key points" of any individual in an image with enough training. These deep learning machines, which have been performing admirably, need a lot of power, which is data. Our model performs better when there is more labelled data available. Google has also experimented with the concept of more data contributing to improved results on a wide scale, with a dataset of 300 million images. Micha Feigin and colleagues (2016) Ultrasound elastography is gaining popularity as a cost-effective and functional diagnostic method for cancer detection and differentiation, as well as thyroid disease diagnosis. 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. Nikhil S. Narayan and colleagues (2016) When an ultrasound wave is stimulated at the region of interest, the amplified back-scatter echo is used to create a brightness picture. 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.* Shekoofeh Azizi and colleagues (2018) *The study of differences in backscattered signals from a tissue over a series of ultrasound frames, known as temporal enhanced ultrasound (TeUS), has previously been proposed as a new paradigm for tissue characterization.* 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. Wenfeng Song *et al.*, (2017) Thyroid ultrasonography is a frequently used clinical procedure for thyroid nodule diagnosis. 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.

4.3.2 Pre-processing data module

Deep learning has truly get the mainstream within the past few years. Deep learning uses neural nets with plenty of hidden layers (dozens in today's state of the art) and requires large amounts of coaching data. These models are particularly effective in gaining insight and approaching human-level accuracy in perceptual tasks like vision, speech, language processing. the idea and mathematical foundations were laid several decades ago. Primarily two phenomena have contributed to the increase of machine learning a) Availability of big data-sets/training examples in multiple domains and b) Advances in raw compute power and also the rise of efficient parallel hardware. Building a good neural network model requires careful consideration of the specification additionally because the computer file format. this text deals with the latter. the foremost common image data input parameters are the amount of images, image height, image width, number of channels, and also the number of levels per pixel. A graphical model of smoking-induced global uncertainty in lung cancer, Yanbo Wang *et al.*, 2015. Typically, there are 3 channels of

knowledge comparable to the colors Red, Green, Blue (RGB) Pixel levels are usually [0,255]. For this exercise let's choose the subsequent values

number of images = 100

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

Uniform aspect ratio: One of the primary steps is to confirm that the pictures have the identical size and ratio. Most of the neural network models assume a square shape input image, which suggests that every image must be checked if it's a square or not, and cropped appropriately. Cropping will be done to pick a square a part of the image, as shown. While cropping, we usually care about the part within the centre.

4.3.3 Thyroid prediction using the architecture

In order to coach the model, we'll be using novel algorithm. In ImageNet, which could be a dataset of over 14 million images belonging to 1000 groups, the model achieves 92.7 percent top-5 test accuracy. It had been one in every of the famous model submitted to ILSVRC-2014. It makes the development over AlexNet by replacing large kernel-sized filters (11 and 5 within the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and it was using NVIDIA Titan Black GPU's.

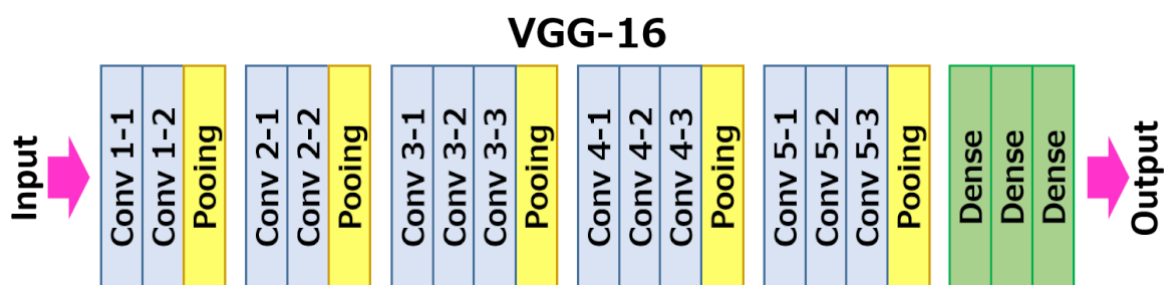


Figure 4.2: VGG-16 Input Output

ImageNet may be a dataset of over 15 million labelled high-resolution images belonging to roughly 22,000 categories. the photographs were collected from the net and labelled

by human labellers using Amazon's Mechanical Turk crowd-sourcing tool. An annual competition called the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) has been held as part of the Pascal Visual Object Challenge since 2010. ILSVRC makes use of a subset of ImageNet, with approximately 1000 images in each of 1000 categories. There are 150,000 training images, 1.2 million validation images, and 1.2 million testing images online. ImageNet is a set of photographs with varying resolutions. Therefore, the pictures are down-sampled to a hard and fast resolution of 256×256 . An oblong image is rescaled, and the central 256×256 patch is cropped out of the resulting image.

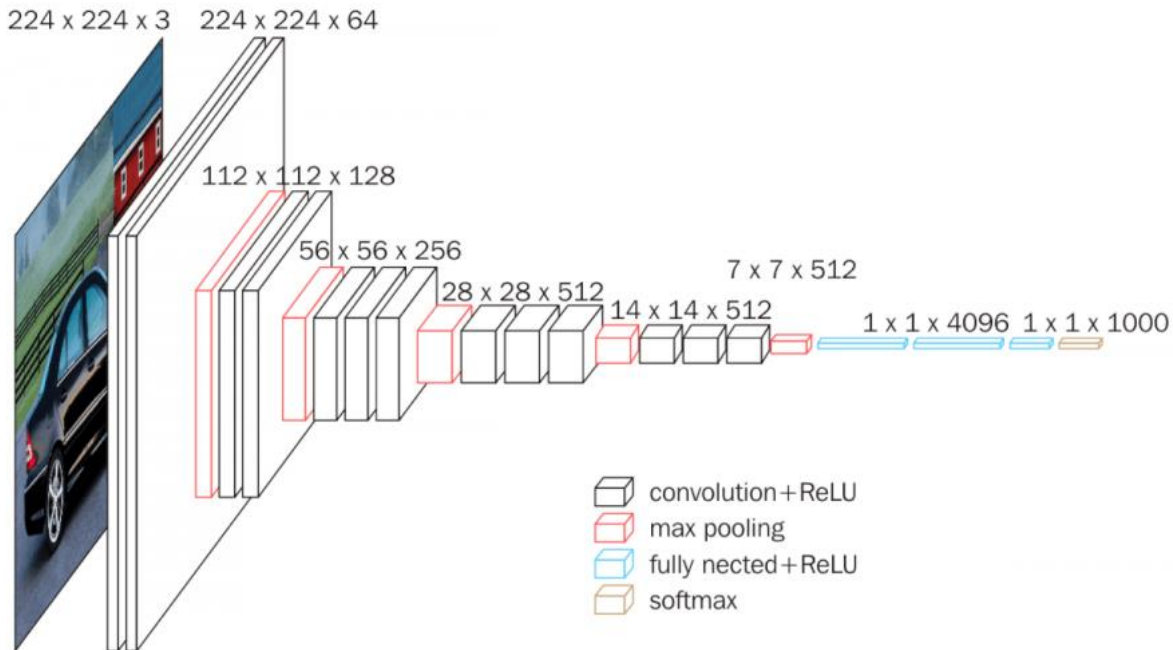


Figure 4.3: Architecture of novel algorithm

The input to cov1 layer is fixed size 224×224 RGB image. The image is more matured a stack of convolutional (conv.) layers, where the filters were used with a really small receptive field: 3×3 (which is that the smallest size to capture the notion of left/right, up/down, center). In one amongst the configurations, it also utilizes 1×1 convolution filters, which may be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed of 1 pixel; the spatial padding of conv. After convolution, the spatial resolution of the layer input is maintained, i.e. the padding is 1-pixel for 3×3 conv. layers. Spatial pooling is allotted by five max-pooling layers, which

follow a number of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over the 2×2 pixel window, with stride 2.

Following a stack of convolutional layers (each with a different depth in various architectures), three Fully-Connected (FC) layers are added: the first two have 4096 channels each, while the third performs 1000-way mapping. ILSVRC is a non-profit organisation that aims to classification and thus contains 1000 channels (one for every class). the ultimate layer is that the soft-max layer. Xiangxiang Zheng *et al.*, Xiangxiang Z (2017) Thyroid Dysfunction Detection with Raman Spectroscopy and an Improved Support Vector Machine at a Low Cost The configuration of the fully connected layers is that the same all told networks.

All hidden layers are the equipped with the rectification (ReLU) non-linearity. it's also noted that none of the networks (except for one) contain Local Response Normalisation (LRN), such normalization doesn't improve the performance on the ILSVRC dataset, but results in increased memory consumption and computation time.'

4.3.4 Database integration

MongoDB could be a cross-platform, document-oriented database that gives, high performance, high availability, and simple scalability. MongoDB works on concept of collection and document.

Database

Database could be a physical container for collections. Each database gets its own set of files on the filing system. one MongoDB server typically has multiple databases.

Collection

Collection could be a group of MongoDB documents. it's the equivalent of an RDBMS table. a group exists within one database. Collections don't enforce a schema. Documents within a group can have different fields. Typically, all documents during a collection are of comparable or related purpose.

Document

A document may be a set of key-value pairs. Documents have dynamic schema. Dynamic schema means documents within the same collection don't have to have the identical set of fields or structure, and customary fields in a very collection's documents may hold differing kinds of knowledge.

The following table shows the relationship of RDBMS terminology with the MongoDB.

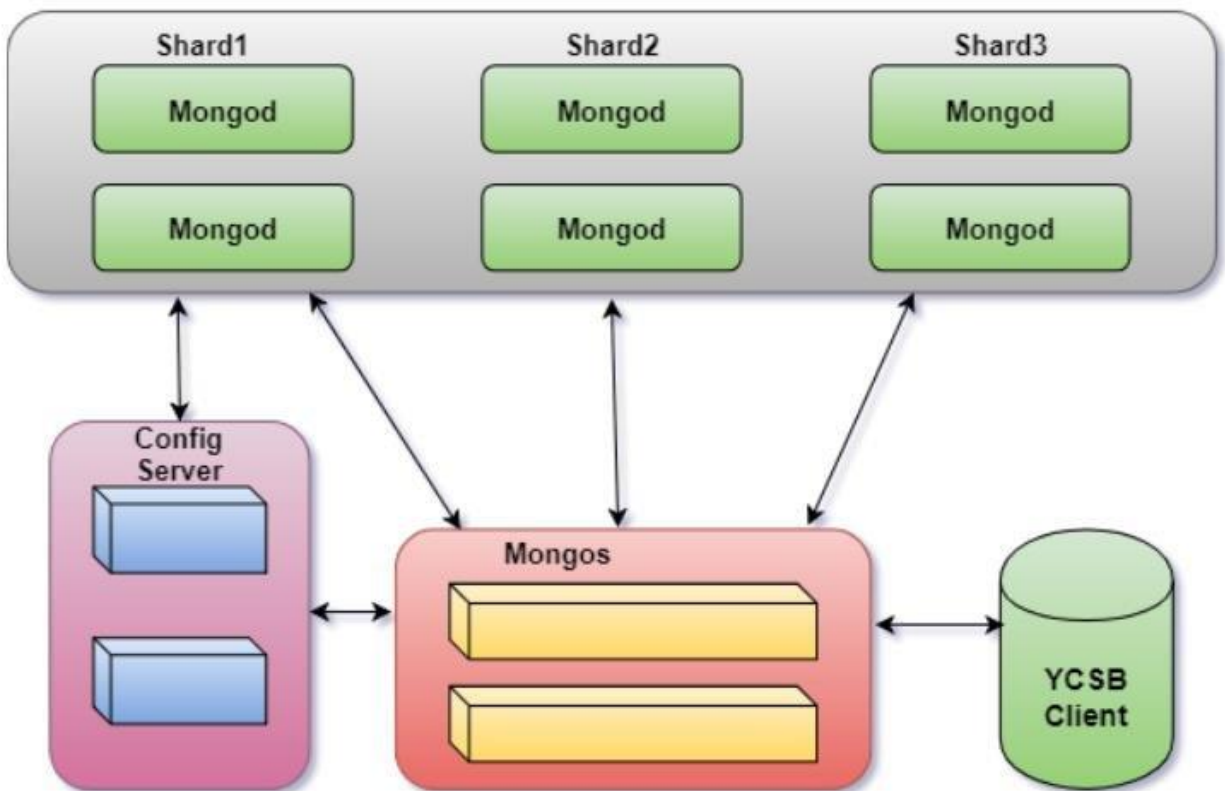


Figure 4.4 Architecture diagram of mongoDB

4.3.5 Web Development

ReactJS is JavaScript library used is for building reusable UI components. per React official documentation, following is that the definition –

React may be a library for building composable user interfaces. It encourages the creation of reusable UI components, which is present data that changes over time. many people use React because the V in MVC. React abstracts away the DOM from you, offering an easier programming model and better performance. React can even render on the server using Node, and it can power native apps using One-way reactive data flow is implemented in React, which eliminates boilerplate and makes it easier to reason about than conventional data binding.

JSX

JSX stands for JavaScript XML. JSX allows us to write down HTML in React. JSX makes it easier to jot down and add HTML in React.

It is faster than normal JavaScript because it performs optimizations while translating to regular JavaScript. Deeply-Supervised Networks with Threshold Failure for Cancer Detection in Automatic Breast Ultrasound, Yi Wang *et al.*, 2019. It makes easier for us to form templates. rather than separating the markup and logic in separated files, React uses components for this purpose. we'll study components in details in further articles.

Components

Components are independent and reusable bits of code. They serve the identical purpose as JavaScript functions, but add isolation and returns HTML via a render function.

Components are available two types, Class components and performance components, during this tutorial we'll consider Class components.

Unidirectional data flow and Flux

React implements one-way data flow which is makes it easy to reason about your app. Flux could be a pattern that helps keeping your data unidirectional.

ADVANTAGES OF REACT JS

Uses a JavaScript object called virtual DOM.

Since JavaScript virtual DOM is faster than the standard DOM, this will increase app speed.

- Compatible with other systems and can be used on both the client and server side.
- Component and data patterns increase readability, allowing for a wider app to be maintained

4.4 SOFTWARE LIST

- Microsoft Visual studio
- Python

4.4.1 Microsoft Visual Studio

Microsoft Visual Studio is the company's integrated production environment (IDE). It is customary to create computer programmes, including websites, web applications, web services, and mobile apps. Microsoft software development tools such as Windows API, Windows Forms, Windows Presentation Foundation, Windows Store, and Microsoft Silverlight are all used by Visual Studio. It can generate both native and controlled code.

Visual Studio comes with a code editor that supports IntelliSense (code completion) as well as code refactoring. The integrated debugger can be used as both a source-level and a machine-level debugger. A code profiler, a designer for creating GUI applications, a web designer, a class designer, and a database schema designer are among the other built-in tools.. It accepts plug-ins that improve functionality on almost every level, including adding support for source control systems (such as Subversion and Git) and new toolsets for domain-specific languages, such as editors and visual designers or toolsets for other aspects of the software development lifecycle (like the Azure DevOps client: Team Explorer).

Visual Studio supports 36 different programming languages and allows the code editor and debugger to support (to varying degrees) nearly any programming language, provided a language-specific service exists. Built-in languages include C, C++, C++/CLI, Visual

Basic NET, C#, F#, JavaScript, TypeScript, XML, XSLT, HTML, and CSS. Support for other languages like Python, Ruby, Node.js, and M among others is obtainable via plug-ins. Java (and J#) were supported within the past.

The most basic edition of Visual Studio, the Community edition, is on the market freed from charge."Free, fully-featured IDE for college kids, open-source, and individual developers," says the Visual Studio Community edition's slogan.

The currently supported Visual Studio version is 2019

Features

Code editor. like every other IDE, it includes a code editor that supports syntax highlighting and code completion using IntelliSense for variables, functions, methods, loops, and LINQ queries.

- Debugger.
- Designer.
- Other tools.
- Extensibility.
- Previous products.
- Community.
- Professional.

4.4..2 Python

In technical terms, Python is an object-oriented, high-level programming language with the integrated dynamic semantics primarily for web and app development. It has a lot of appeal in the field of Rapid Application Development because it allows for dynamic typing and binding.

Python is comparatively simple, so it is easy to be told since it requires a singular syntax that focuses on readability. Developers can be read and translate Python code much easier than other languages. In turn, this reduces the price of program maintenance and development because it allows teams to figure collaboratively without significant language and skill barriers.

Additionally, Python supports the utilization of modules and packages, which suggests that programs will be designed during a modular style and code may be reused across a

spread of projects. Once you've developed a module or package you wish, it are often scaled to be used in other projects, and it is easy to import or export these modules.

One of the foremost promising benefits of Python is that both the quality library and therefore the interpreter are available freed from charge, in both binary and source form. there's no exclusivity either, as Python and every one the mandatory tools are available on all major platforms. Therefore, it's a tasty option for developers who don't desire to stress about paying high development costs.

If this description of Python over your head, don't fret. You'll comprehend it in time. What you would like to require removed from this section is that Python could be a artificial language accustomed develop software on the net and in app form, including mobile. It's relatively easy to be told, and also the necessary tools are available to all or any freed from charge.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 RESULTS

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. A web application using reactJS is developed to upload the scanned image. Various datasets were collected and one example among the collected dataset can be found below

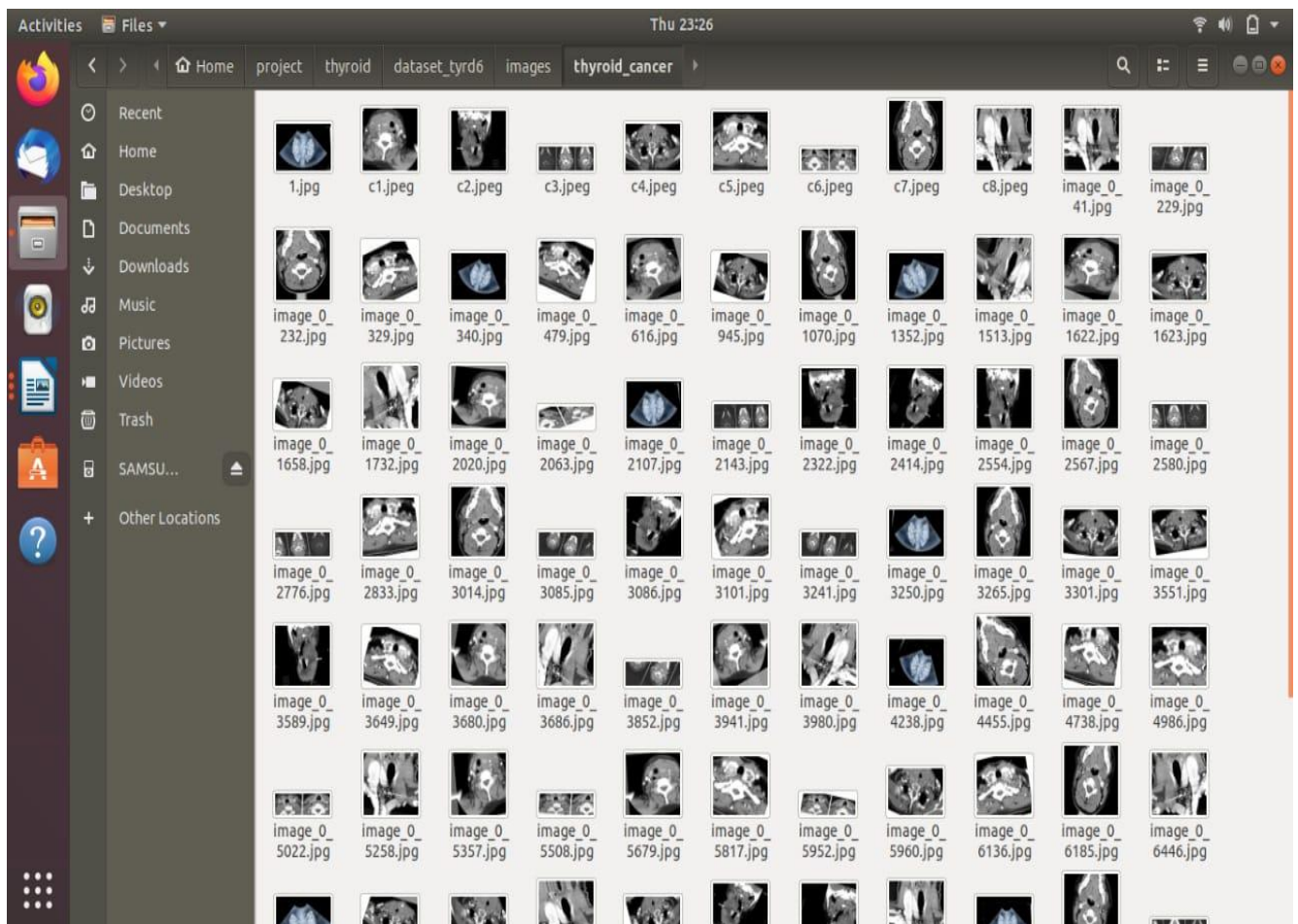


Figure 5.1 Dataset Collected

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 5.2 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 is can be seen in the following figure below

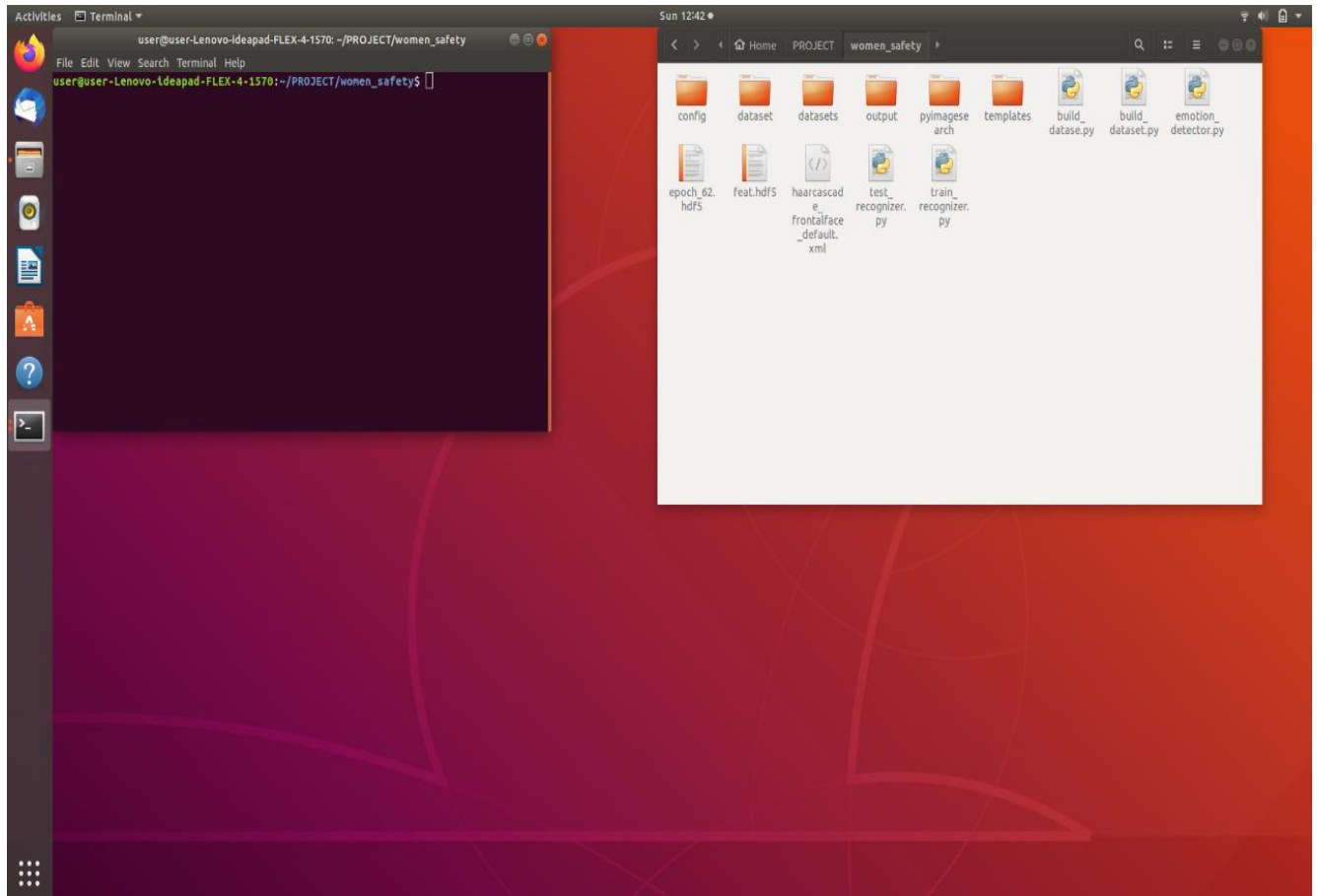


Figure 5.3 Moving Inside the Coding Folder For Execution

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

```
Activities Text Editor Wed 15:08
thyroid_6types.txt
Save

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 5.4 Efficiency of Model Obtained

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



Figure 5.5 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

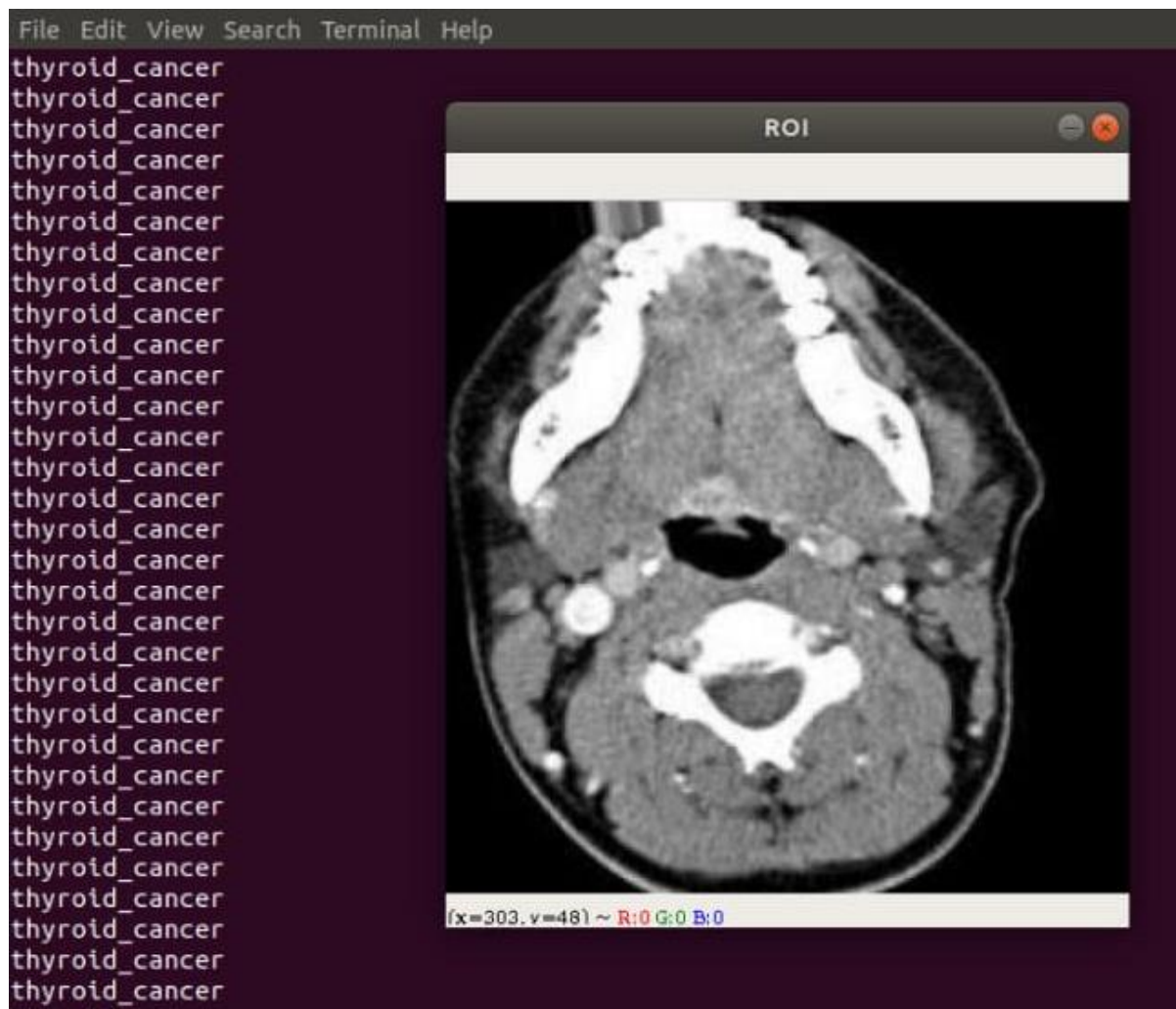


Figure 5.6 Thyroid Cancer Prediction



Figure 5.7 Thyroiditis Prediction



Figure 5.8 Normal Thyroid Prediction

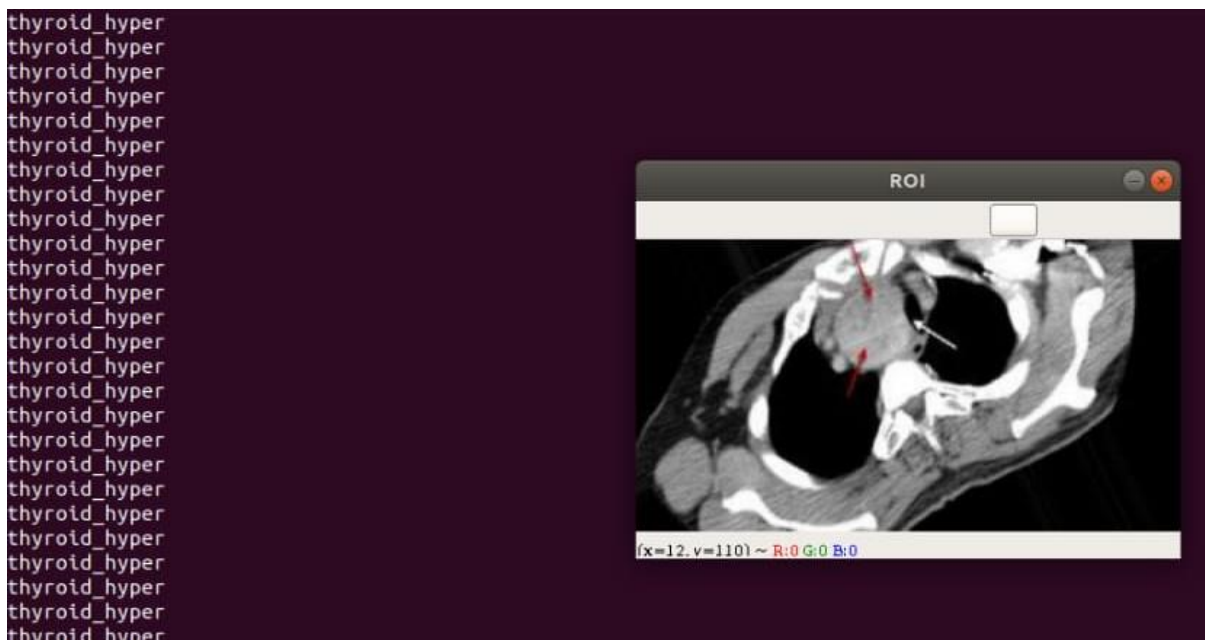


Figure 5.9 Hyperthyroid Prediction

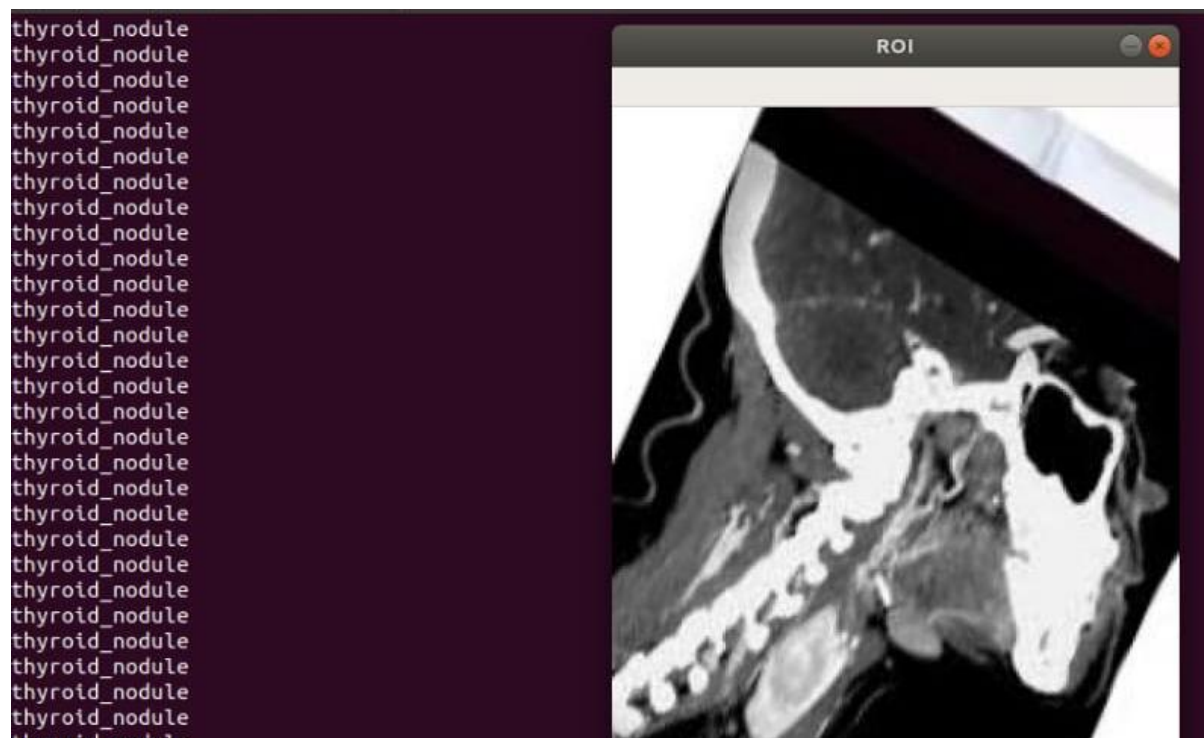


Figure 5.10 Thyroid Nodule Prediction

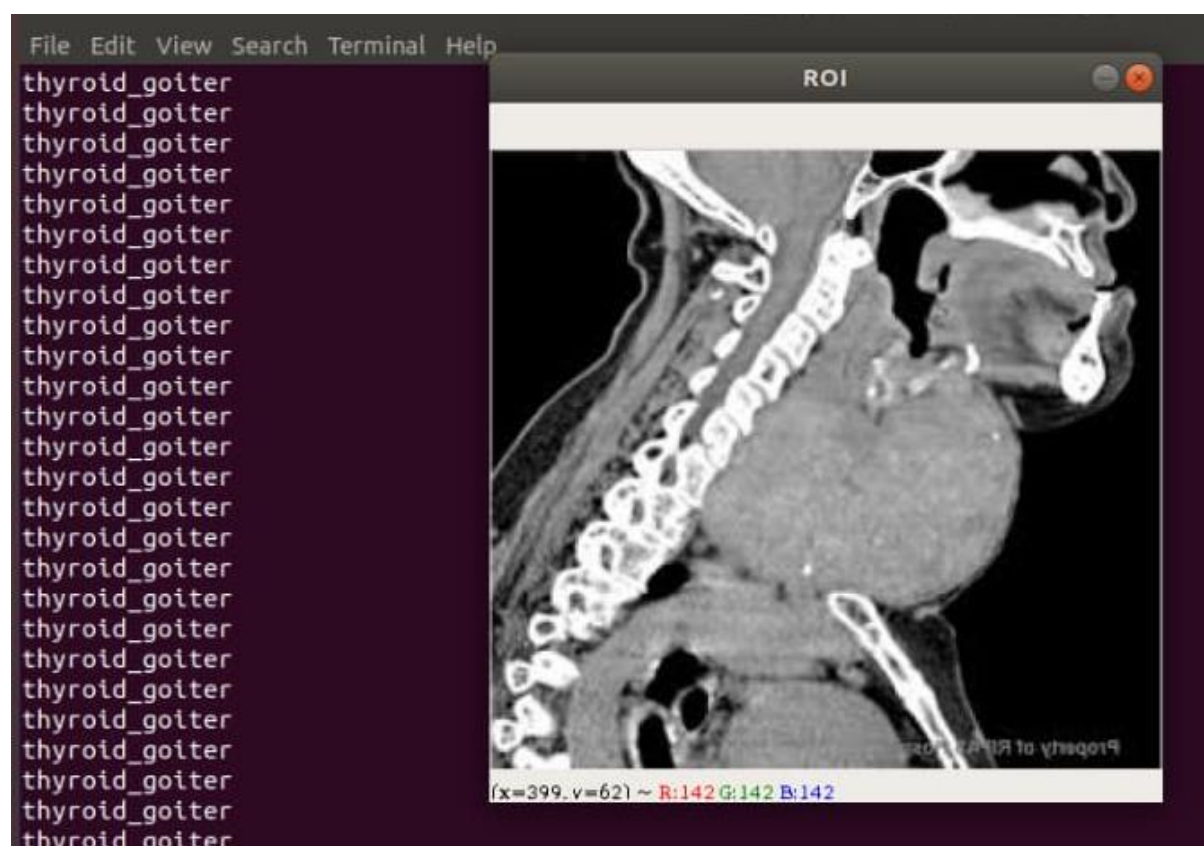


Figure 5.11 Goitre Prediction

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 is displayed to the user interactively.

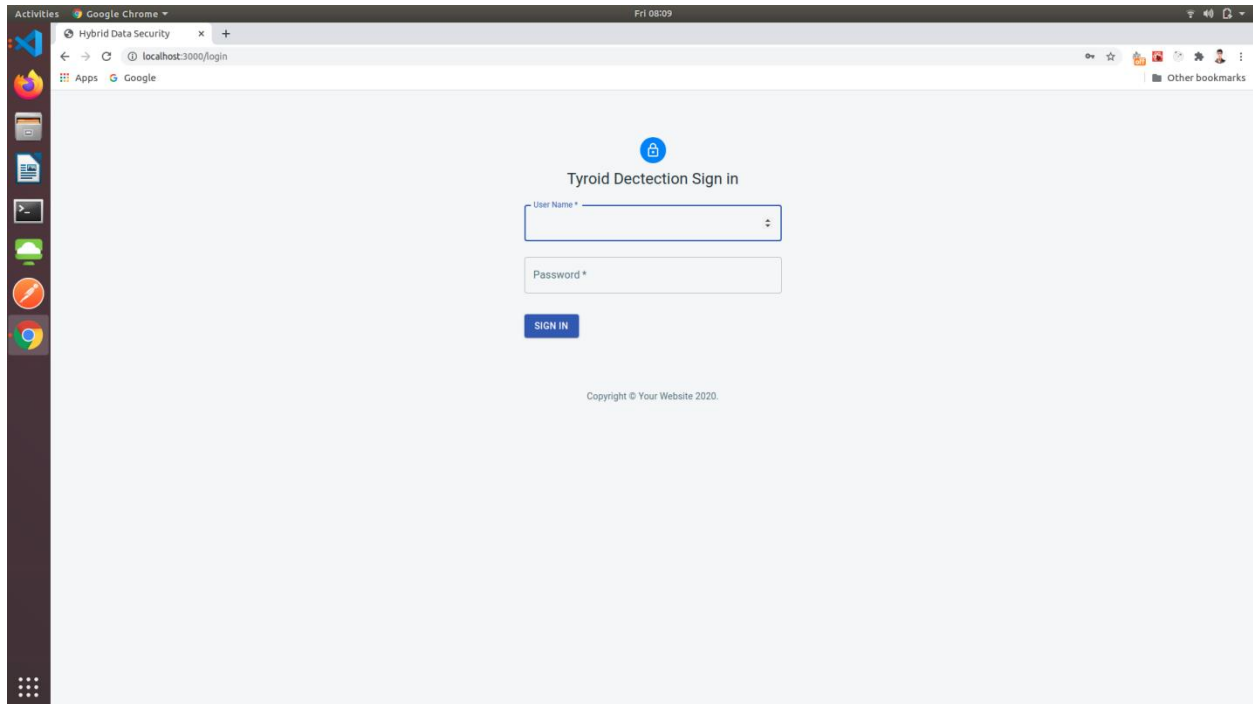


Figure 5.12 Thyroid webpage login page

The user the signs in to his/her account, to perform the diagnosis.

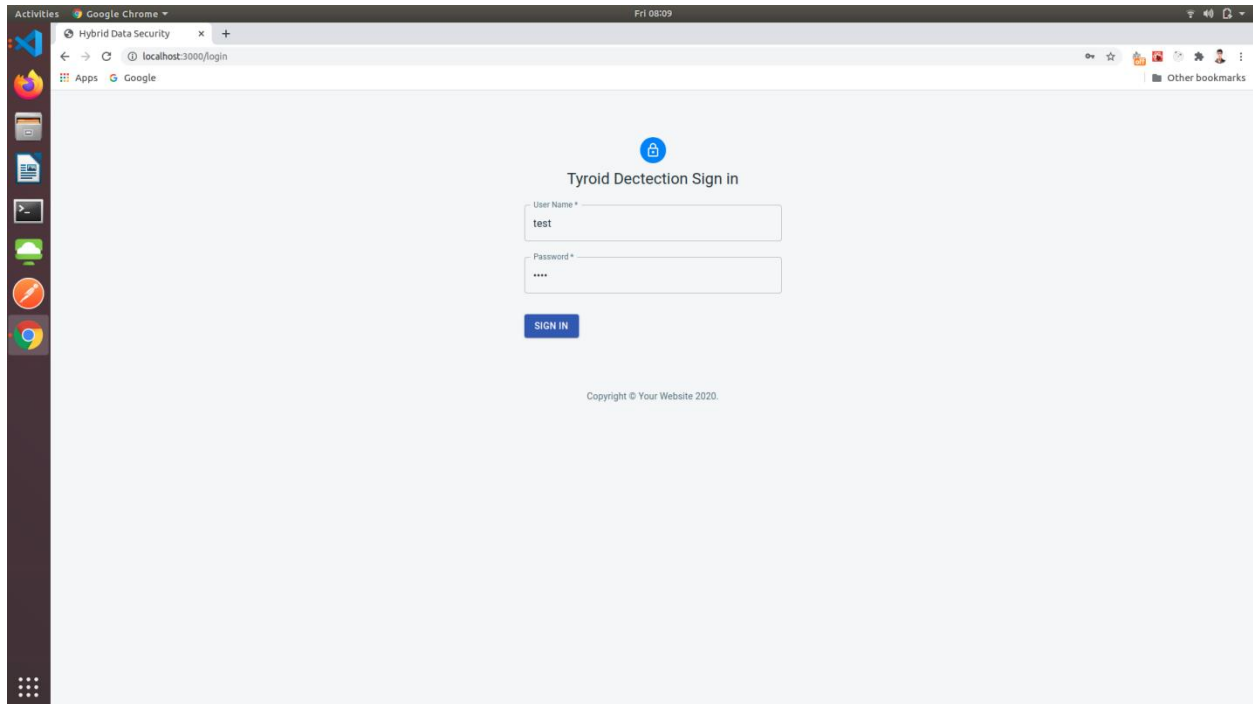


Figure 5.13 Thyroid sign-in page

Once the user has successfully logged in ,the home page is displayed to the user

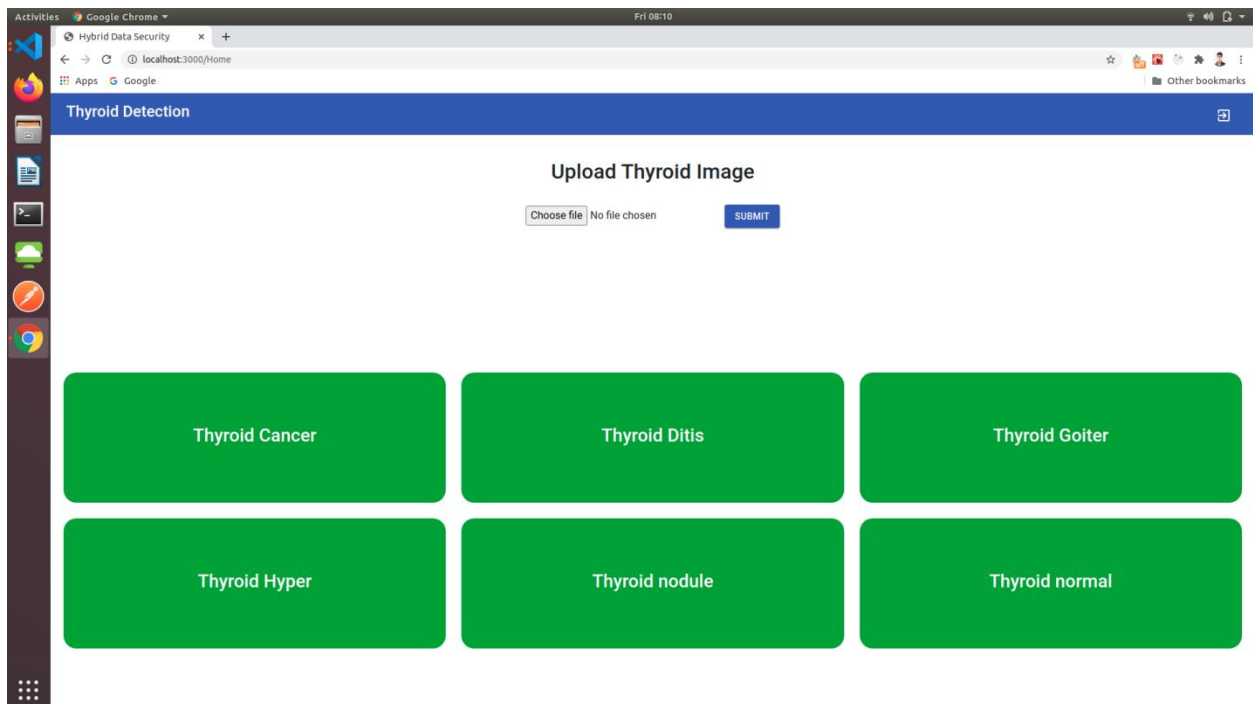


Figure 5.14 Sign-in successful

The user can then upload the images through the webpage.

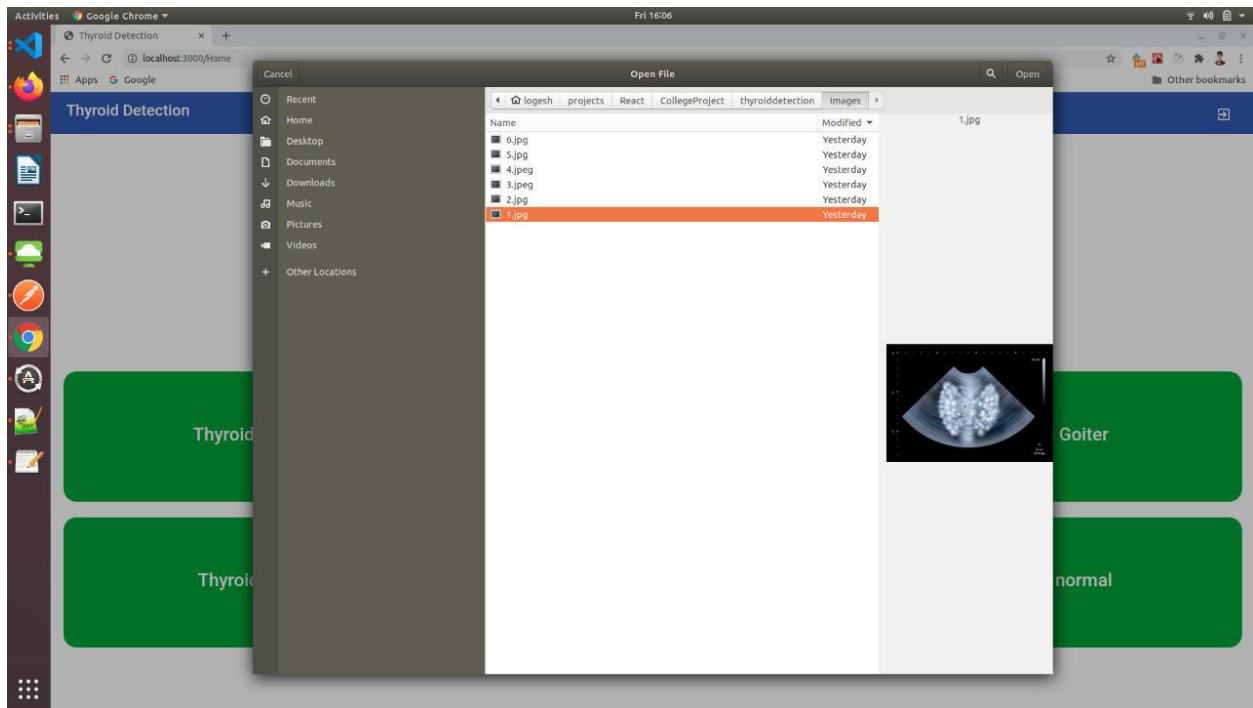


Figure 5.15 Image upload

The user can view the type of thyroid disease the patient is suffering from.

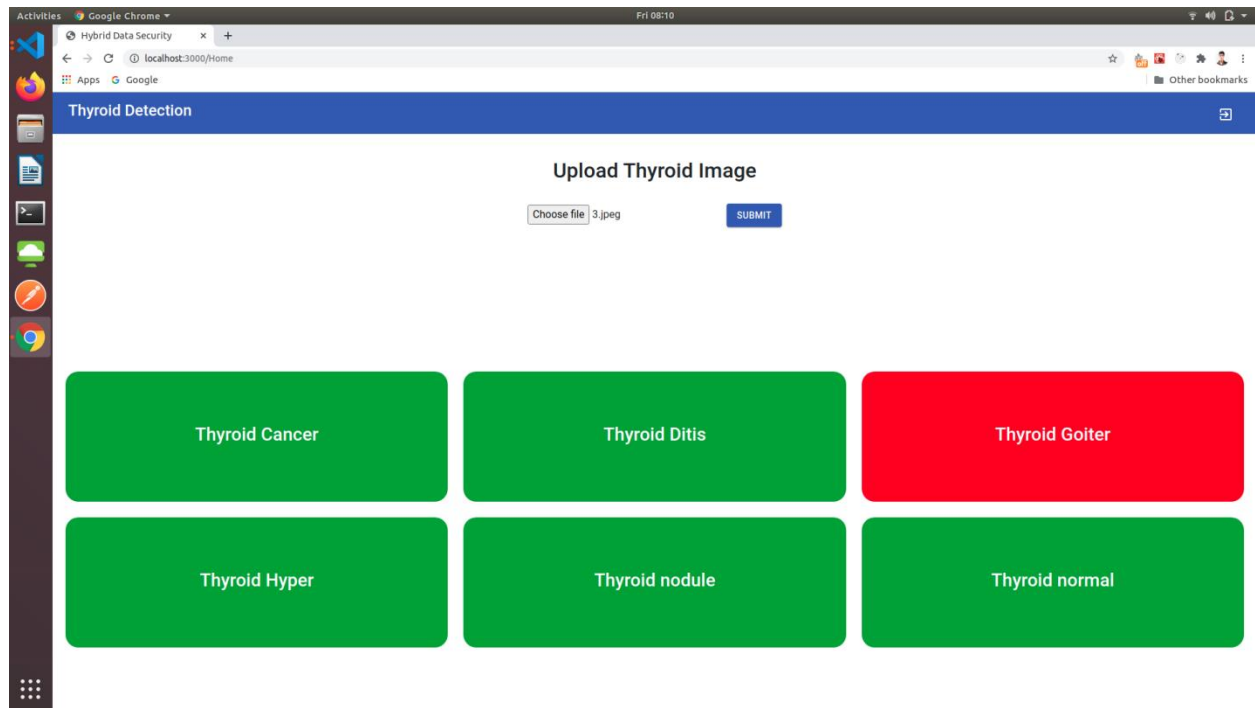


Figure 5.16 Results

Thus, from the above results and discussion, it is clear that we have efficiently made a project for predicting the different kinds of thyroid diseases with a web application using reactJS to upload the image and to view the diagnosis interactively. Thus, we have successfully implemented the scope of the project.

6.2 DISCUSSION

In the existing system, the transfer learning only works if the initial and target problems of both models are similar enough. If the primary round of coaching data required for the new task is simply too off from the info of the old task, then the trained models might perform worse than expected. Only benign and malignant variety of thyroid presence is detected within the existing system. Accuracy decreases with decrease within the amount of knowledge. within the proposed system, we've overcome the disadvantages of the prevailing system by the implementation of the online application to see the first prediction of thyroid diseases. we've achieved an accuracy of 99% thus, eliminating the human error rate.

FACTORS	EXISTING SYSTEM	PROPOSED SYSTEM
ALGORITHM	Online Transfer Learning (OTL)	VGG16, ResNet algorithms
ACCURACY	Very low compared to other state-of-art methods	Has very high accuracy of 99%
USER-FRIENDLY	The system is not user friendly.	The system is very user friendly uses a web application as interface.
APPLICATION	The method is applicable only for diagnosis of two type of thyroid diseases.	The method is applicable only for diagnosis of six types of thyroid diseases.

CHAPTER – 6

SUMMARY AND CONCLUSION

6.1 SUMMARY

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. A data set is a set of information. Deep Learning has emerged as the preferred tool for tackling a wide range of difficult real-world problems. It is, without a doubt, the most effective approach for computer vision tasks. Deep learning's strength in computer vision is demonstrated in the picture above. A deep network can segment and classify the "key points" of any individual in an image with enough training.

6.2 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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APPENDIX

```
# construct the image generator for data augmentation

aug = ImageDataGenerator(rotation_range=30, width_shift_range=0.1,
    height_shift_range=0.1, shear_range=0.2, zoom_range=0.2,
    horizontal_flip=True, fill_mode="nearest")

# grab the list of images that we'll be describing, then extract
# the class label names from the image paths

print("[INFO] loading images...")

imagePaths = list(paths.list_images(args["dataset"]))

classNames = [pt.split(os.path.sep)[-2] for pt in imagePaths]

classNames = [str(x) for x in np.unique(classNames)]

# initialize the image preprocessors

aap = AspectAwarePreprocessor(64, 64)

iap = ImageToArrayPreprocessor()

# load the dataset from disk then scale the raw pixel intensities to
# the range [0, 1]

sdl = SimpleDatasetLoader(preprocessors=[aap, iap])

(data, labels) = sdl.load(imagePaths, verbose=500)
```

```

data = data.astype("float") / 255.0

# partition the data into training and testing splits using 75% of
# the data for training and the remaining 25% for testing
(trainX, testX, trainY, testY) = train_test_split(data, labels,
                                                  test_size=0.25, random_state=42)

# convert the labels from integers to vectors
trainY = LabelBinarizer().fit_transform(trainY)
testY = LabelBinarizer().fit_transform(testY)

model = ResNet.build(64, 64, 3, 7, (3, 4, 6),
                    (64, 128, 256, 512), "dataset_tyrd6/images")

# loop over all layers in the base model and freeze them so they

print("[INFO] compiling model...")
opt = Adam(lr=0.001)
model.compile(loss="categorical_crossentropy", optimizer=opt,
              metrics=["accuracy"])

# start to become initialized with actual "learned" values

```

```

# versus pure random

print("[INFO] training head...")

model.fit_generator(aug.flow(trainX, trainY, batch_size=32),
                    validation_data=(testX, testY), epochs=20,
                    steps_per_epoch=len(trainX) // 32, verbose=200)

# evaluate the network after initialization

print("[INFO] evaluating after initialization...")

predictions = model.predict(testX, batch_size=32)

print(classification_report(testY.argmax(axis=1),
                             predictions.argmax(axis=1), target_names=classNames))

print("[INFO] re-compiling model...")

opt = SGD(lr=0.0001)

model.compile(loss="categorical_crossentropy", optimizer=opt,
              metrics=["accuracy"])

# train the model again, this time fine-tuning *both* the final set
# of CONV layers along with our set of FC layers

print("[INFO] fine-tuning model...")

H = model.fit_generator(aug.flow(trainX, trainY, batch_size=32),
                        validation_data=(testX, testY), epochs=15,
                        steps_per_epoch=len(trainX) // 32, verbose=1)

```

```

for key in H.history.keys():
    print(key)

# evaluate the network on the fine-tuned model
print("[INFO] evaluating after fine-tuning...")
predictions = model.predict(testX, batch_size=32)
print(classification_report(testY.argmax(axis=1),
    predictions.argmax(axis=1), target_names=classNames))

# save the model to disk
print("[INFO] serializing model...")
model.save(args["model"])

plt.style.use("ggplot")
plt.figure()

plt.plot(np.arange(0, 15), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, 15), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, 15), H.history["acc"], label="train_acc")
plt.plot(np.arange(0, 15), H.history["val_acc"], label="val_acc")
plt.title("Training Loss and Accuracy on PADDY")
plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy")
plt.legend()
plt.savefig(args["output"])

```