Thyroid Malignancy Detection

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Abstract : Thyroid Cancer is highly fatal and often diagnosis is time consuming due to the requirement of multiple tests and biopsies. In this project, this observation has been taken into consideration and a technique has been proposed that will present a more objective and accurate classification and would further offer a valuable second opinion to medical practitioners. A classifier is used that extracts features that quantify changes in the texture characteristics of the training images from both benign and malignant nodules. The resulting feature vectors are used to train the classifier. A VGG-16 model that is pre-trained on the ImageNet dataset is fine tuned using thyroid ultrasound images to classify malignant and benign lesions. This system is expected to be fast while being accurate at the same time in order to be useful in scenarios requiring speedy diagnosis and treatment.

Index Terms - Thyroid Malignancy, Deep Learning, Convolutional Neural Networks, Transfer Learning

I. INTRODUCTION

Thyroid cancer arises from an atypical growth of thyroid tissue at the thyroid gland's edge. Initially, in the throat a lump is formed and an overgrowth of this tissue leads to the formation of benign or malignant thyroid nodules. The incidence of Thyroid cancer has been increasing since the past three decades. Some investigators have stated that Thyroid Cancer is often over-diagnosed and under many circumstances it is not detected until the life-threatening stage. Nodular thyroid disease is common, and because of the associated risk of malignancy and hyperfunction, these nodules have to be examined thoroughly. The risk of developing a palpable thyroid nodule in a lifetime ranges between 5% and 10%. Thyroid ultrasonography is preferred choice for thyroid nodule imaging as it is, does not use harmful ionizing radiation, and has a relatively shorter acquisition time compared to other modalities like Computed Tomography and Magnetic Resonance Imaging. However, these images contain echo perturbations and speckle noise which could make the diagnosis difficult. The limitations of ultrasonography were a motivation to develop cost-effective, non-invasive, and accurate thyroid diagnosis support systems that output reproducible objective classification results. This project will combine the topics and techniques from various subjects such as Digital Image Processing, Artificial Intelligence and Deep Learning. The Deep Convolutional Neural Network (DCNN) classifier will be trained on sonographic images and will be the core of the project. For preprocessing and feature engineering, the project will need to utilize digital image processing techniques such as image augmentation, segmentation and filtering amongst others. This will fine tune the classifier and improve performance.

II. LITERATURE SURVEY

Shah J. P. (2015).[2] The incidence of thyroid cancer has risen in recent years. In the United States, the incidence increased at an annual rate of 5.4% in men and 6.5% in women from 2006 to 2010. Whether this increase represents a true presence and rise in incidence, or early discovery of subclinical disease-is totally a matter of discussion. Early diagnosis of subclinical diseases are also becoming more common throughout the world. This increase in early diagnosis of diseases has thus generated a significant interest in the management of thyroid cancer.

Lina Pedraza, Carlos Vargas, et al.[3] Studied the open access Thyroid ultrasound dataset provided by the University of Columbia and determined the need for using data augmentation techniques and transfer learning which is typically used to prevent the model from overfitting. The method constituted training a CNN from scratch using the medical data. The layer architecture is 3 Convolutional Layers with 3x3 kernels of numbers 32, 32 and 64 respectively. The features from the fully-connected (FC) layer were classified using a regular sigmoid function into the two classes benign or malignant. The training of the CNN was done on the GPU and since the model is relatively shallow and the dataset small, the training completed in an hour's time.

U. Rajendra Acharya , S. Vinitha Sree, M. [4] Features that quantify the local changes in the texture characteristics of the ultrasound off-line training images from both malignant and benign nodules were extracted. Subsequently, to predict the class of a new on-line test thyroid ultrasound image the feature vector-classifier combination that results in the maximum classification accuracy was used. Two data sets with 3D Contrast- Enhanced Ultrasound (CEUS) and 3D High Resolution Ultrasound (HRUS) images of 20 nodules (ten malignant and ten benign) were used. A novel integrated index called Thyroid Malignancy Index (TMI) was proposed using the combination of FD, LBP, LTE texture features, to diagnose benign or malignant nodules. This index can assist clinicians to make a more objective differentiation of malignant or benign thyroid lesions.

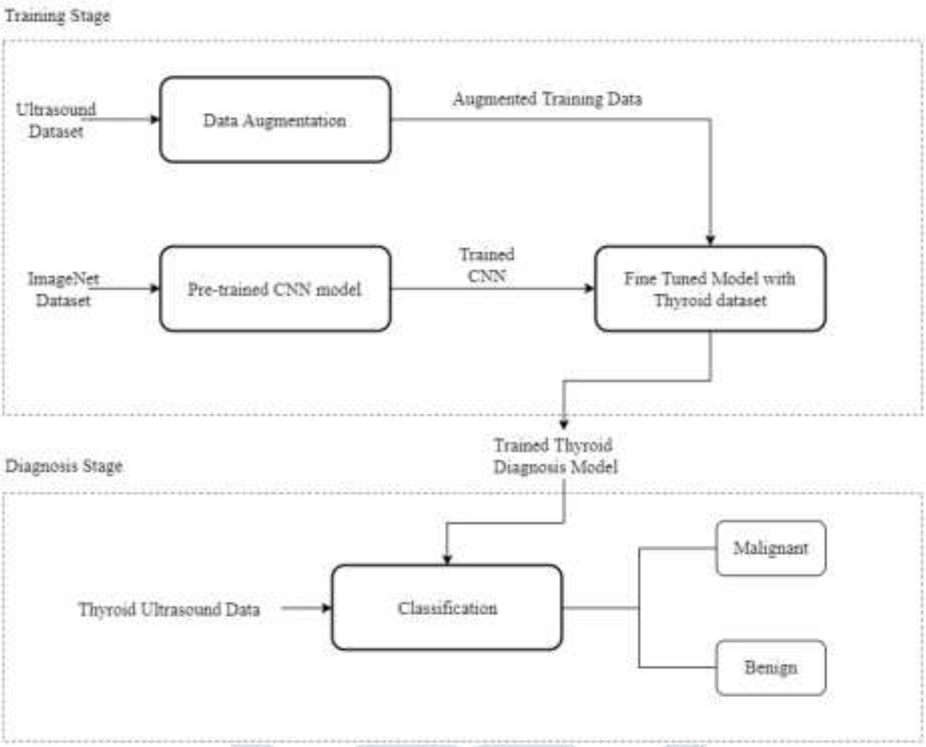
Chi, Jianning [5] This paper presents a computer-aided diagnosis (CAD) system for classifying thyroid nodules in ultrasound images. Deep learning approach was used to extract features from thyroid ultrasound images. Ultrasound images are pre-processed to calibrate their scale and remove the less significant features. A pre-trained GoogLeNet model is then fine-tuned using the image samples that are pre-processed which leads to superior feature extraction. The features that were then extracted from the thyroid ultrasound images are sent to a cost-sensitive Random Forest classifier which classifies the images into "benign" and "malignant" cases respectively.

Gao Huang, Zhuang Liu [6] Recent work has shown that convolutional neural networks can be significantly deeper, more accurate, and better efficiency to train if they contain shorter connections between layers close to the input and the output layers. In this paper, Dense Convolutional Network (DenseNet) is introduced, which connects each layer to every other layer in a feed-forward fashion. While traditional convolutional neural networks with N layers have N connections - one layer between each layer and then its subsequent layer - this network has N(N+1)/2 direct connections[6]. The feature-maps of all preceding layers are used as inputs for each layer, and its own feature-maps are used as inputs for the next layers. DenseNets have several credible advantages: they strengthen feature propagation, reduce the vanishing-gradient problem, encourage feature reuse, and substantially reduce the number of parameters. The proposed architecture is evaluated on four highly competitive object recognition benchmark tasks namely SVHN, ImageNet, CIFAR-100, and CIFAR-10. DenseNets obtain significant improvements over the latest architectures on most of them, while requiring less computation to achieve higher performance.

Image Classification task of a Machine Learning/Deep Learning algorithm is widely found to be useful in the medical imaging domain wherein the algorithm is trained to classify medical images into benign or malignant in case of cancer detection and various other ailments based on the symptoms in the images. In work associated with computer vision and biomedical imaging, the availability of medical data is limited. When running a deep learning algorithm with millions of parameters, less data hurdles the training with overfitting.

The model eventually tends to fail at generalization of learning giving low accuracy on the test dataset. Regularization can reduce the high variance to some extent but training a deep learning framework from scratch remains out of bounds. Data augmentation can be applied to the dataset to further augment the dataset size. Therefore, in order to get accuracies which can be of deployment standard, a method of training a smaller convolutional neural network from scratch, transfer learning-using bottleneck features from deep convolutional neural networks to train a new layer or a different classifier and finally fine-tuning deep architectures to classify the custom dataset is used.

III. BLOCK DIAGRAM



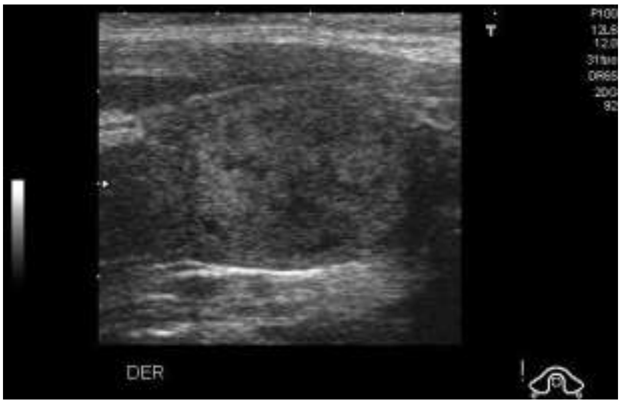
- Data augmentation : The Thyroid ultrasound dataset is processed using data augmentation techniques and fed to the fine tuned model.
- Pre - Trained Model : The weights from a pre - trained neural network are used in the current model.
- Fine - Tuned Model : The ImageNet classifier is fine tuned to recognise Thyroid images using the dataset.

IV. DATASET DESCRIPTION

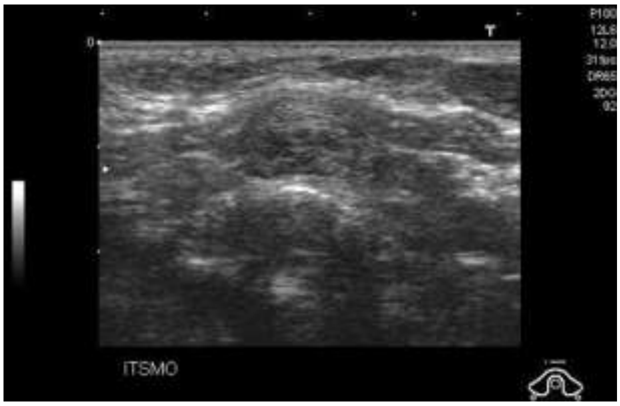
The dataset is a publicly available one consisting of 400 images and their corresponding biopsy verified reports in .xml format. Pedraza et al. [2015]. Each of the images is given a TIRADS score from 2 to 5 on the scale of probability of malignancy. Since our task in this work dealt only with benign or malignant test scenarios, only scores 2 and 3 were considered as benign and all the scores above these as malignant.

IV.I Thyroid Imaging Reporting and Data Systems (TIRADS)

Thyroid nodules are very common, occurring in up to 50% of people in the United States[2]. The concern of any nodule is whether it is a thyroid cancer. Fortunately, approximately 95% of thyroid nodules are benign. Currently, the only way to diagnose thyroid cancer prior to surgery is with thyroid biopsy. Thyroid ultrasound plays an important role in identifying a nodule and the visual on ultrasound along with the size are the major factors deciding the need for biopsy. With increase in the suspicious features of the thyroid nodule, the threshold for thyroid biopsy is lowered. A lot of research is being done to develop a system for assessing the risk of cancer based on ultrasound alone. The Thyroid Imaging Reporting and Data Systems (TIRADS) is a 5 point classification which helps to determine the risk of cancer in thyroid nodules based on ultrasound characteristics observations. This system has been mainly used for thyroid nodules that are ≥1 cm. This study explores the accuracy of TIRADS to predict cancer in thyroid nodules that are less than or equal to 1 cm.



Sonographic image of non malignant thyroid nodule (TIRADS 2)



Sonographic image of malignant thyroid nodule (TIRADS 4a)

V. Implementation

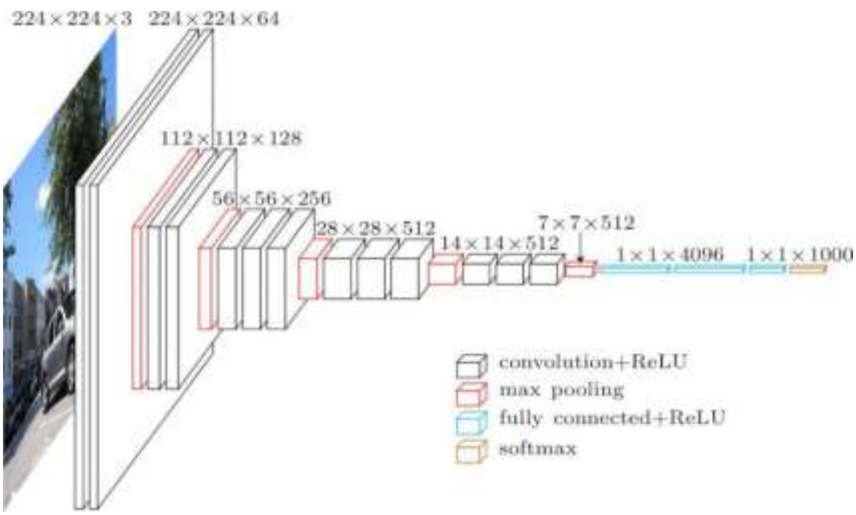
The project was implemented in two phases or modules. The first module consisted of building a deep learning classifier to distinguish between the malignant and benign thyroid nodules. This module forms the core part of the application which is responsible for the correct diagnosis of images. For this a technique known as transfer learning was used on a VGG-16 model pre-trained on the ImageNet Database and fine tuned with the ultrasound image dataset. The second phase of the project comprises the development and deployment of the system in the form of a web application which can be accessed by medical professionals. This part was implemented using the django framework based on python as python supports the deep learning libraries required as well. The users are able to upload their thyroid ultrasound images through this platform to the server and obtain their results. Also, the system then stores the data with the user's approval for further training.

V.I Algorithm:

- Provide input image into convolution layer.
- Choose parameters, apply filters with strides, and padding. Perform 2D convolution on the image and apply Rectified Linear Unit activation to the matrix.
- Perform pooling to reduce dimensionality size.
- Apply batch normalization and dropout for speeding up the calculation.
- Flatten the output and then feed into a fully connected layer.
- Output the class using an activation function (Logistic Regression with cost functions) and classify images.

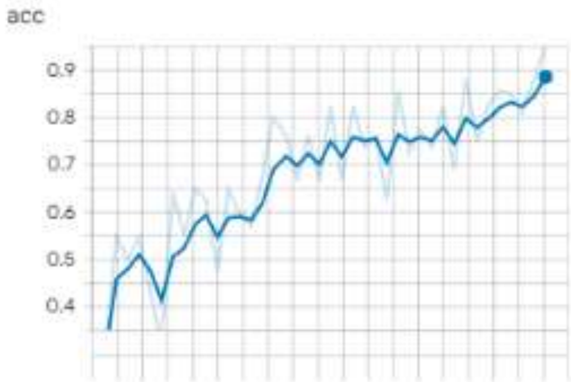
V.II. VGG-16 Architecture

VGG-16 is a 16 layer model trained on 14 million images from ImageNet dataset to recognize an image from one of the 1000 categories with an accuracy of 92.5%. We used this model further to classify images in two classes relevant to our problem which is benign or malignant thyroid tumors and thus output a vector of 2 values. VGG-16 is preferred as it can run on low computational devices too. Various filters are used with fully connected layers and a softmax layer to normalize the classification vector.

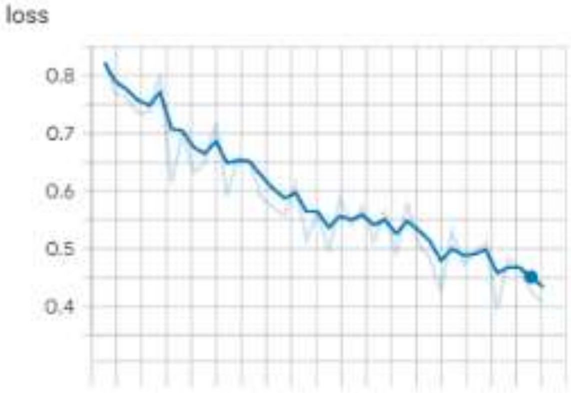


VI. RESULTS

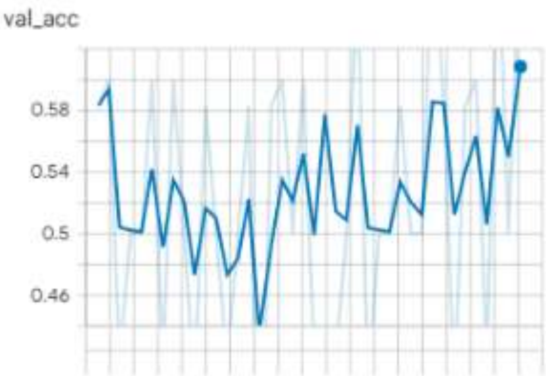
Accuracy :



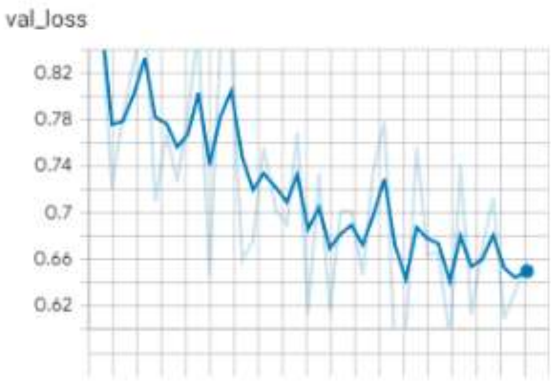
Loss :



Validation Accuracy :



Validation Loss :



VII. CONCLUSION

The diagnosis of Thyroid Nodules using ultrasound images and the computer aided diagnosis techniques (CAD) for the same has been studied. The techniques that are currently available are either too expensive, complex or are intrusive for the human body due to the use of radioactive materials. Implementation of a deep learning classifier that will overcome all these limitations of the current diagnosis techniques is done. Data augmentation is used before training in order to have a more robust classifier. Data augmentation is a technique used to train the classifier when the amount of data available is less. In data augmentation, some simple transforms to the images from the existing dataset were applied. Even though they are the same images, the classifier “perceived” them as different images. Some examples of transforms studied are translating, rotating, shearing, flipping the image, cropping, padding etc. Due to this, the dataset size increased by a factor of the number of transformations used. The algorithm identified informative image regions and used the informative regions and assigned a reliable malignancy score where higher values correspond to higher malignancy scores. The metrics used for evaluating the aforementioned methods are accuracy i.e. ratio of the total number of correct predictions to the total number of images predicted, sensitivity, which gave an indication of true positive rate and specificity for true negative rate. The classification was done on the dataset separately. It was observed that the public dataset gave high sensitivity and low specificity. This is due to the nature of the data wherein the public dataset consisted of biased data with a number of cancerous samples on the higher side. This problem was handled by data augmentation achieved by flipping, rotating and adding noise to the existing images. Even though data augmentation helps alleviate the problems caused by smaller datasets, it is not enough to get the maximum potential out of the classifier. Therefore, typically, a technique known as transfer learning was used. In transfer learning, pre- existing or pre-trained weights were used. Here, the weights from a previously trained model were used to train a new model. The weights that are trained on existing datasets such as ImageNet were loaded into the model after which the model was fine tuned using the smaller dataset to recognize thyroid images.

This helped with dataset limitations and computational limitations to a great extent. Further, a simple web app was designed to utilize features of the convolutional neural network model to make detections.

VIII. ACKNOWLEDGMENT

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