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# 3. Thyroid Nodule Identification in Ultrasound Images using CNN

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## ABSTRACT

Early detection of any disease assists in reduction of disease progression. In this work discrimination of the thyroid nodules is studied by employing deep learning architectures. Deep learning algorithm mimics the function of the human cerebral cortex. Convolutional Neural Network (CNN) is based on deep neural network design which has many hidden layers that are used to train a large dataset.

When the number of hidden layers is increased, it has a greater impact on the accuracy. In this study, CNN is employed for assessing the severity of the disease. In CNN, the output of the input layer is fed the convolutional layer followed by ReLU layer and Max pooling layer and the images are classified into Benign (TI-RADS 2, TI-RADS 3, TI-RADS 4a) and Malignant (TI-RADS 4b, TI-RADS 5, TI-RADS 6).

The performance of CNN is compared with the pre-trained networks such as Alex net, VGG-19 and Resnet-50 using transfer learning. The CNN outperformed the pre-trained networks with an accuracy of 99.17%.

**KEYWORDS**

Thyroid nodule, Convolutional Neural Network, transfer learning

## Introduction

The occurrence of thyroid nodules is common and the evaluation of these incidents is done by ultrasound (US). US provides fast and safe method of examination, moreover it does not involve any harmful radiation.

US have become the appropriate diagnostic tool in the identification of anomalies [Cheng Xie et al 2016].

In previous Computer Aided Diagnostic (CAD) tools the output relies on the manually extracted features and processing of such features are tedious and difficult [D. Yi et al, 2017].

To overcome this drawback an alternative method is proposed to learn features from whole images directly through a CNN [S.-C. B. Lo et al., 1995]. Many classification tasks have been performed well by CNN.

The three major classifications of CNN that are applied to medical images are CNN trained from scratch, pre-trained CNN employed to extract features from the image and fine tuning the pre-trained model [Shuyue Guan et al., 2017].

In this study, the CNN is trained from the scratch without dropout layer and compared with the transfer learning algorithms to detect the thyroid nodules using publicly available database.

Increasing the number of layers does not lead to over-fitting or degradation; it leads to the training error [Kaiming He et al., 2016].

## Thyroid Imaging Reporting & Data System (Ti-Rads)

Fig.1. shows the distribution of the Digital Database for Thyroid Ultrasound Images (DDTI) dataset [cimalab.intec.co/applications/thyroid].

- **TI-RADS 1:** Normal thyroid gland
- **TI-RADS 2:** Benign conditions (0% risk of malignancy)
- **TI-RADS 3:** Probably benign nodules (<5% malignancy)
- **TI-RADS 4:** Suspicious nodules (5-80% malignancy)
- **TI-RADS 4a:** Undetermined (5-10% malignancy)
- **TI-RADS 4b:** Suspicious (10-80% malignancy)
- **TI-RADS 5:** Probably malignant nodules (>80% malignancy)
- **TI-RADS 6:** Biopsy proven malignancy

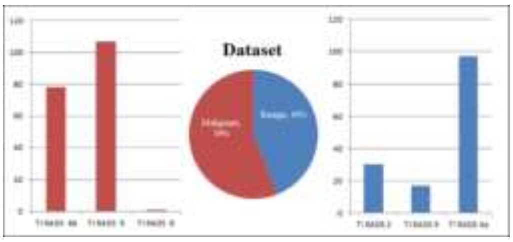



**Fig 1: DDTI Dataset Distribution**

## Overview of Thyroid Anatomy

The thyroid gland is located in the neck region and it is highly vascular. It extends from the fifth cervical vertebrae to the first thoracic. Fig.2. describes the thyroid glands anterior and lateral views [http://msk-anatomy.blogspot.com/2013/06/thyroid-gland-anatomy.html, 2013]. Thyroid nodules are those which are formed in the organ as fluid or solid filled lumps. Most of the thyroid nodules do not cause symptoms and do not need treatment; however, in severe cases it needs medical attention. The treatment may include medication or surgery, hence correct diagnosis is required.

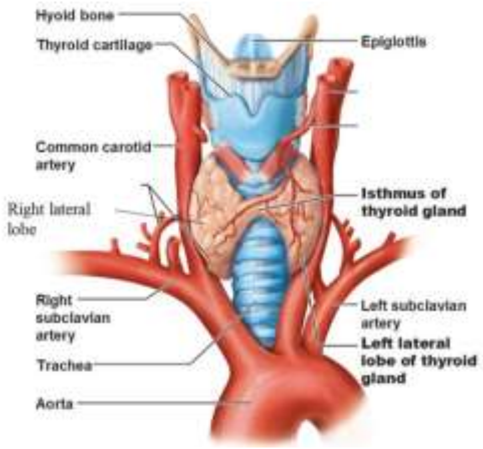



**Fig.2. Thyroid gland, anterior and lateral views, adapted from** [msk-anatomy.blogspot.com/2013/06/thyroid-gland-anatomy.html, 13 June 2013].

## Ultrasound

Ultrasonic waves are generally referred to as high frequency sound waves that are not in the audible range of human hearing. The frequency of ultrasonic waves ranges from 20 KHz up to several gigahertz. Though they have several applications, they are highly recommended in medical imaging. They are used in imaging fetus in the mother's womb and most predominantly in the cancer diagnostics. As they do not radiate any harmful radiation, it is considered as the safest imaging technique. They are also used in therapeutic procedure, breaking of stony deposits or tissues, accelerating the functioning of drug distribution inside the body.

The main principle of ultrasound is the "Piezo-electric effect" wherein the electric energy is converted to sound energy; this sound energy is conveyed through the tissues (area of interest) and is reflected back. The reflected signal is then captured by means of transducer and it is converted back to electrical signal. Finally ultrasound image is obtained pertaining to the received electrical signal. Fig.3. shows the block diagram of the principle of Piezo-electric effect. Radiologists are always looking for a solution to minimize the radiation dosages for imaging procedures; ultrasound is considered since it is non-invasive, cost effective and lacks radiation. The newer application of ultrasound includes 3D imaging, laparoscopic ultrasound, shear wave elastography and development of wireless transducers.

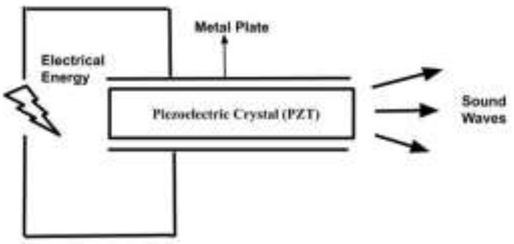



**Fig 3: Principle of Piezo-Electric Effect**

The better iteration of latest technologies, progressive improvements and the overall development cost of ultrasound systems are much less compared to other modalities, this has been a prime factor in choosing the ultrasound systems. Ultrasound is more reproducible and productive as they reduce the need for operator skill in real-time volumetric scanning.

The diagnostic conclusions are easier because of the improved contrast agents and increased spatial resolutions [expresshealthcare.in/specials/in-imaging-specials/recent-advances-in-ultrasound-imaging-technology, 2020].

The rest of this paper is sectioned as follows. Section II briefly describes about some previous relevant works on classification of nodules, tumors, lesions and other abnormalities in imaging examinations using machine learning models and deep learning approaches. In Section III the image processing technique that is implemented to classify the thyroid nodule is discussed followed by transfer learning techniques in Section IV, results and discussions in Section V and conclusion in Section VI.

## Related Work

The features of the image were extracted using the feature cropping method and hybrid multi class CNN was used for the classification of thyroid nodule. Classification accuracy of 96.12% was achieved using DDTI dataset [Ruoning Song et al., 2020]. A deep learning technique was proposed by fine tuning the CNN – resNet-50. The proposed method outperformed the VGG-19 model [Olfa Moussa et al., 2019]. The development of a classification model for detecting papillary thyroid cancer with an improved accuracy using ultrasound images was done using Python programming technique using DDTI dataset [Ashok Kumar et al., 2020].

The approaches for the automatic thyroid nodule classification in ultrasound image was reviewed and concluded that CNN performed well. Computer Aided Diagnosis (CAD) is the future diagnostic tool [Deepika Koundal et.al 2012]. Each parameter on the performance of the network was explained. If the number of hidden layers is increased the time required for the computation is more, thereby increasing the time required to train the network [Saad ALBAWI et al., 2017]. Transfer learning in CNN was applied to detect breast cancer from mammograms. A combination of VGG network and neural network yielded better result [Shuyue Guan et al., 2017]. A brief survey was done by a set of scientist to discover the correct diagnosis of the thyroid nodule detection by the radiologists as well as the CAD system. The reference incurred that CAD system performed well when compared to the radiologists [Tingting Li et al., 2020].

CNN for the detection of thyroid nodules from thermo graphic images was implemented. Three CNN networks namely Alex Net, Google Net and VGG network were trained and their accuracy was calculated based on their performance comparison on the nodule detection. The Google Net CNN yielded the highest accuracy (86.22%) followed by Alex Net (77.67%) and the VGG (74.96%) [M. B. H. Moran et al., 2017]. CNN was used to find generic features in endoscopy images, in order to detect lesions. The image used was extracted from gastrointestinal examinations obtained by gastroscopy. The authors used the features extracted from the developed CNN and it was fed to the Support Vector Machine (SVM) to enhance the method generalization ability. The proposed method outperformed the other methods based on color and texture features [Rongsheng Zhu et al., 2015].

A system based on the analysis in the spatial and frequency domain was experimented. The diagnosis of the malignant tumor nodule was done using artificial intelligence. Weighted binary cross entropy function was used. The spatial domain analysis using deep learning techniques and the frequency domain analysis by Fast Fourier based methods was used [Dat Tien Nguyen et.al. 2020]. The CNN model for traffic sign classification by using "fine tuning" technique was trained. Longer time was required to train the network if the batch size was large and it also affected the memory size.

Fine tuning technique was employed to reduce the time needed to train [Nadia Jmour., 2018]. Various pre-trained CNN network architecture like Alex Net, Google Net, Dense Net, Squeeze Net, ResNet, VGGNet etc was tested for detecting the disease in mango and potato leaf. They concluded that Alex net architecture outperforms the CNN architecture [Sunanyana Arya & Rajeev Singh 2019].

A deep learning technique was developed to classify the thyroid nodule with 762 images. The over-fitting of the images was corrected using data augmentation technique and global average pooling. VGG-16 model was used and obtained 0.916 as the area under the curve [Soon Woo Kwon et al., 2020]. A novel deep learning based CAD system was proposed for the automatic detection of nodules and classification using neural networks. The CAD system consisted of two stages; first it detected the pyramidal features for detecting nodules and then a multi-branch classification network was used for the multi-view diagnosis. Two different types of datasets were used and their detection and diagnostic accuracy was 97.5% and 97.1% respectively [Liu, T et al., 2019]. A new transfer learning technique was identified to diagnose fault using TranVGG 19 as the feature extractor. VGG-19 has been used in applications such as image classification, speech recognition and pattern recognition. The dropout technique was introduced in the fully connected layer for training. The training time was 200 seconds and the model achieved an accuracy of 99.175% [Long Wen et al., 2019].

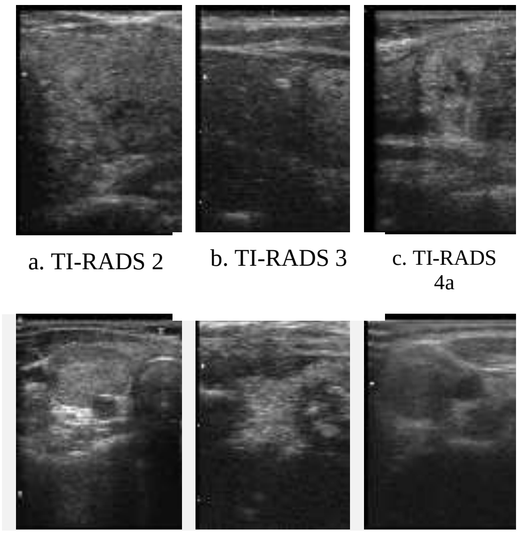
The fish image was classified into six classes using Resnet-50 architecture, because the traditional CNN required larger database which was not available. The accuracy achieved was 97.19% and it was a time saving process. Different frozen layer performance along with the number of samples was also evaluated [Yaxin Ma et al., 2018]. The training of the deep neural networks was difficult. In order to ease the training: residual learning framework was proposed. The proposed residual network was easy to optimize and the accuracy was increased by increasing the depth of the layers. ResNet architecture of layer 18 and 34 was employed for the classification of the Image net and CIFAR-10 dataset [Kaiming He et al., 2018]

## Thyroid Nodule Detection in Us Images

### Dataset

The Digital Database of Thyroid ultrasound Images (DDTI) is an open access resource. It consisted of 328 images which are categorized into six classes.

The training and the test set distribution are 278 train images and 50 test images. The size of the image is 360 x 560x 1 which is given as input to the network. The network classifies the labels into classes from 1-6.



a. TI-RADS 2 b. TI-RADS 3 c. TI-RADS 4a

d. TI-RADS 4b e. TI-RADS 5 f. TI-RADS 6

**Fig.4 Sample images from DDTI dataset**

Fig.4 shows the benign (TI-RADS 2, TI-RADS 3, TI-RADS 4a) and malignant (TI-RADS 4b, TI-RADS 5, TI-RADS 6) nodule sample images that has been taken from the publicly available database "Digital Database of Thyroid ultrasound Images" (DDTI).

## CNN Models

Large convolutional networks perform incredibly well, however the reason for their performance is yet to be identified. CNN are deep neural networks that train the images by convolving the input image with filters or kernels to extract the features. An image of M x N is convolved with a filter f x f to extract the feature from the entire image [Zeiler, M. D. and Fergus 2014]. The feature maps are studied when the window slides after each operation. In order to preserve the size of the image and the edges, padding is used. CNN has many applications in object detection, image recognition and so on.

## CNN Model for DDTI Dataset

The CNN model for the DDTI dataset is shown in Fig.5. The input image is of the size 360 x 560 x 1. The input is converted to RGB image and is fed to the convolutional layer along with the filter. By local receptive field the feature maps are extracted. The ReLU layer is the next layer in the model, which implements the activation function and describes about the positive part of its argument. The pooling layer follows the ReLU layer; there are three types of pooling namely: Max, Average and Sum. In this study Max pooling layer is implemented. In the fully connected layers there are six definite output classes. Finally, the fully connected layer is connected to the max pooling layer to the output neurons in the model. The parameter setting of the proposed model is,

- Batch size: 278 (training), 50 (testing)
- Number of epochs: 20
- Learning Rate: 0.0001
- Softmax Probability: 0.9

ReLU is the popular activation function that is being used now-a-days in the architecture of CNN. The result of the activation function is either 0 or positive integer. It is easier to train a large dataset using ReLU.

Fig 5 shows the block diagram of the proposed CNN model without the dropout layer where S denotes the Stride of pooling.

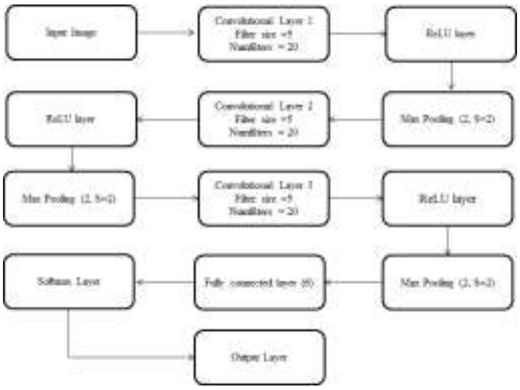



**Fig.5 CNN model for DDTI dataset**

## Transfer Learning

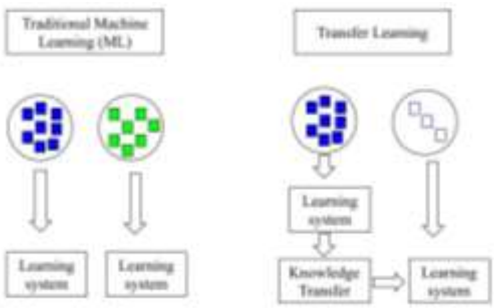



**Fig.6. Transfer learning versus Machine learning**

Transfer learning is considered as the key to general intelligence.

In computer vision, a neural network detects the edges in earlier layers, shapes in the middle layer and in the latter layer some specific tasks are carried on. In transfer learning, only the initial and the middle layers are used and the latter layers are retrained.

In transfer learning, much knowledge is transferred from the previous learning system to the newly developed system. This knowledge depends on the problem and the data. Fig 6 shows the difference from the conventional machine learning technique to that of the transfer learning method.

The benefit of using the transfer learning technique is that it saves the training time and the data required to train the network need not be large. Hence in places where there are only a few data available for training, transfer learning is considered as the best tool for classification.

In this paper three transfer learning techniques have been implemented, namely: Alex net, VGG-19 and ResNet 50. Basic considerations for the images include:

- **Training**: 278 images
- **Validation**: 30% of the training set of images
- **Testing**: 50 images
- **Learning** Rate: 0.0001
- **Epoch**: 20

## ALEXNET

The Alex net architecture was proposed by Alex Krizhevesky in 2012. Alex net architecture attained a state-of-art recognition accuracy against all other traditional deep learning network and computer vision approaches [Md Zahangir Alom et al., 2018]. The architecture of Alex net is shown in Fig.7.

Alex net architecture has three convolutional layers and two fully connected layers. The initial convolution layer performs convolution, Maximum Pooling function with Local Response Normalization (LRN) in which 96 filters were used with 11x11 dimensional matrices. With stride size of 2 and 3x3 filters mask the max pooling operation is done. This same operation was performed in the next layer with 5x5 filter. 3x3 filter mask is implemented in the third, fourth and fifth layer with 384, 384 and 256 feature maps respectively.

Two fully connected layers along with the dropout layer are implemented with each of 4096 feature maps followed by the Softmax layer.

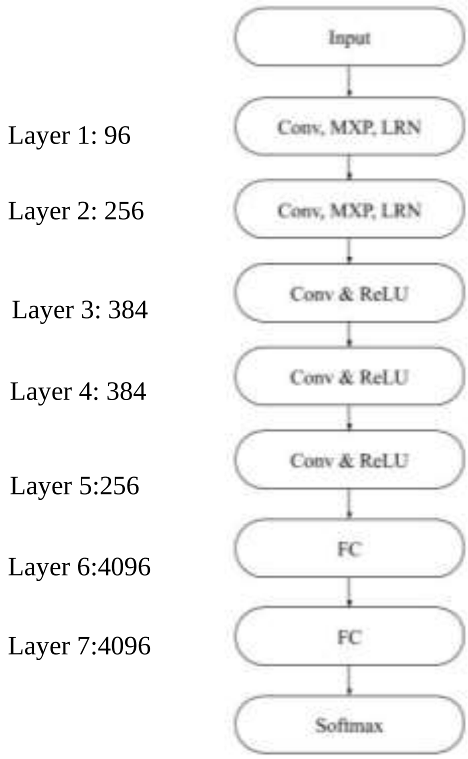



**Fig.7 Architecture of Alex Net: Convolution, Max-Pooling, LRN and fully connected (FC) layer**

## RESNET 50

ResNet architecture was designed by Kaiming He in 2015. In order to address the problem of vanishing gradient which the predecessors had, Kaiming He has implemented the ultra-deep network. ResNet has been developed with different layers namely 34, 50, 101, 152 and even 1202.

In Resnet-50 there are 49 convolutional layers and 1 fully connected layer [Md Zahangir Alom et al., 2018]. The basic block diagram of ResNet is shown in Fig.8.

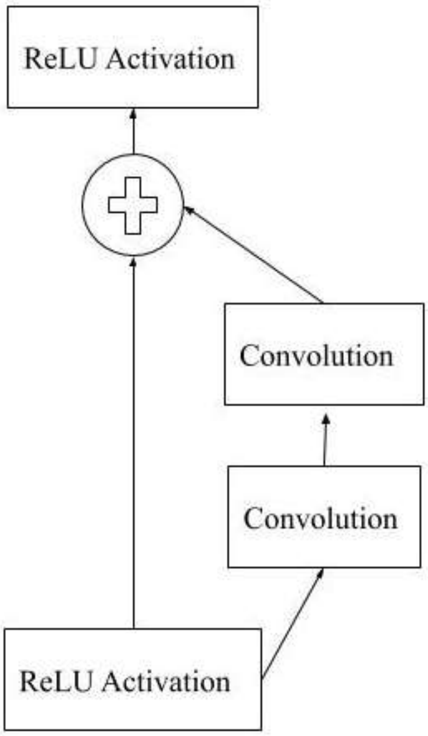



**Fig.8. Basic diagram of Residual Block**

ResNet is a feed forward network with inbuilt residual connection. The final output of the residual network can be defined by the equation 1.

$$x_l = F\ (x_l - 1) + (x_l - 1) \quad (1)$$

Deep Residual network is nearly similar to the networks having convolution, pooling, activation function and fully connected layers which are stacked over one another. The identity connection is the term which makes the residual network unique from the other networks. The addition of the identity connection does not require any additional parameters; hence the computational complexity is same as in the case of simple deep networks. The dimensional value of x and F must be same for performing the addition operation.

In the architecture of ResNet 50 there are four stages. This architecture first performs the convolution operation followed by the max pooling with the kernel sizes of 3x3 and 7x7. For deeper networks like Resnet-50 and Resnet-152 bottleneck design is used. Each residual function is stacked over one another. The three convolution layers are 1x1, 3x3 and 1x1. The 1x1 convolution layer is responsible for reducing and restoring the dimensions. Finally the 3x3 layer is the bottleneck with smaller input or output dimensions.

## VGG-19

The Visual Geometry Group (VGG) network proved that for better accuracy and recognition in CNN, the depth of the layer is considered as the critical component [Md Zahangir Alom et al., 2018]. This network was proposed by Karen Simoyan and Andrew Zisserman in 2014. This network architecture consists of two convolutional layers and they both employ the ReLU activation function. All models in VGG net have three fully connected layers at the end. VGG-19 is considered as the most computational expensive model which contains 138M weights. The architecture of VGG-19 is shown in the Fig.9.

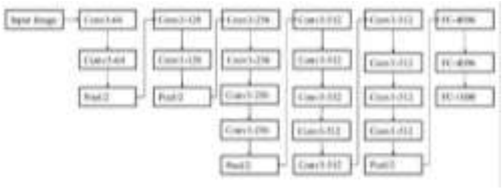


**Fig.9. Architecture of VGG-19 – 3 fully connected layers**

In VGG-19 there are 16 convolutional layers and 3 fully connected layers in total 19 layers.

It consists of 2 fully connected layers with 4096 channels and followed by another fully connected layer with 1000 channels, so that 1000 predictions can be done with the labels.

The final fully connected layer uses Softmax layer for the classification purpose.

## Result Analysis

The proposed work is implemented using MATLAB 2020a. Primarily the training phase of the proposed model is shown in Fig.11.

An accuracy of 99% is achieved in the training phase with a minimum batch loss. Followed by the second figure,

Fig.12 shows the training phase of Alex net architecture,

Fig.13 shows the training phase of ResNet 50 model and finally Fig.14 shows the training phase of VGG-19 model.

From the results obtained, it is observed that the training accuracy increases with the increase in epoch's (Fig 10). From the Fig 10, it is evident that by increasing the epoch the accuracy is increased and also the time taken for the training.

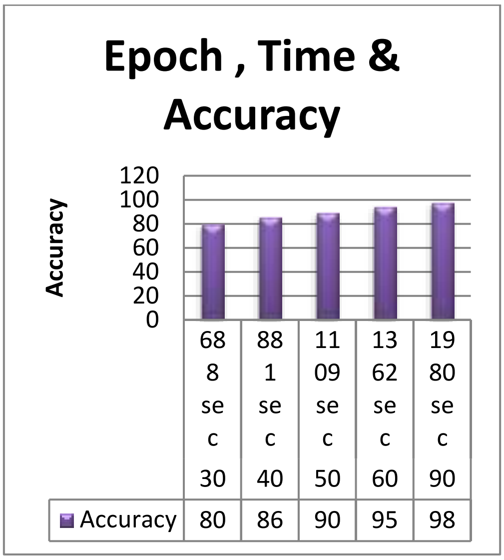



**Fig.10. Comparison of Epoch, Time and Accuracy**

The training progress of the proposed CNN, Alex net, ResNet 50 and VGG 19 is shown in Fig.11 to Fig 14.

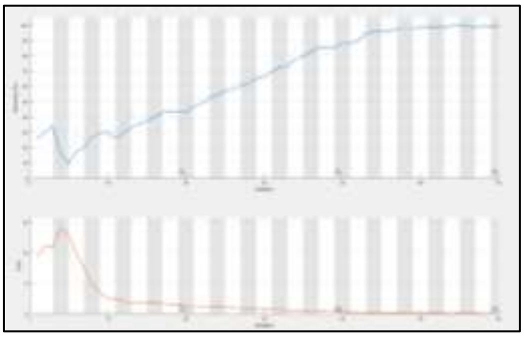


**Fig.11 Training progress of CNN**

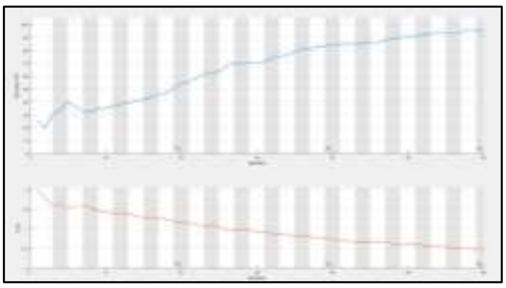


**Fig.13. Training progress of ResNet 50**

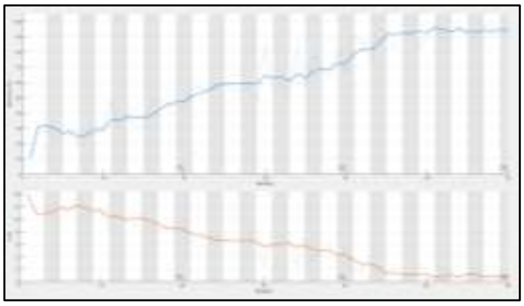


**Fig.14. Training progress of VGG 19**

From the results it is observed that

- When the CNN network is trained with 20 epochs' in the initial training phase, 99.17% accuracy is achieved with a batch loss of 0.1321, learning rate of 0.0001. 278 images were considered for training and 30% of the training data is considered for the validation. 30 images were taken for testing.
- When the Alex Net network is trained with 20 epochs' in the initial training phase, 97.667% accuracy is achieved with a batch loss of 0.3736, learning rate of 0.0001. 278 images were considered for training and 30% of the training data is considered for the validation. 30 images were taken for testing.
- When the Resnet 50 network is trained with 20 epochs' in the initial training phase, 96.88% accuracy is achieved a mini batch loss of 0.4982, learning rate of 0.0001. 278 images were considered for training and 30% of the training data is considered for the validation. 30 images were taken for testing.
- When the VGG-19 network is trained with 20 epoch's in the initial training phase, 93.75% accuracy is achieved with a batch loss of 0.9964, learning rate of 0.0001. 278 images were considered for training and 30% of the training data is considered for the validation. 30 images were taken for testing.

**Accuracy and Loss**

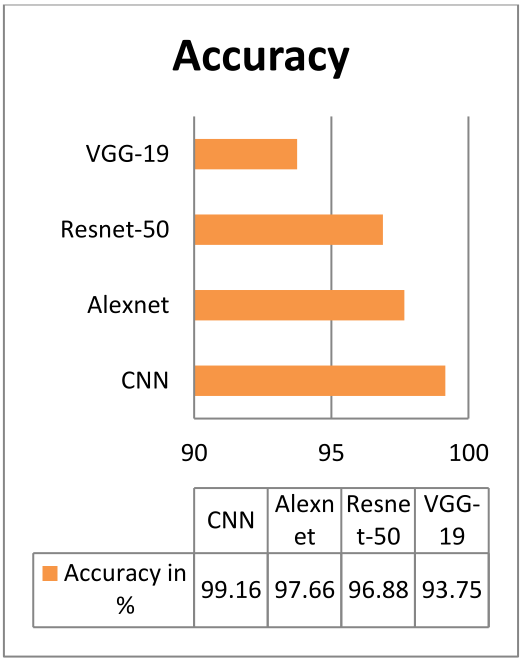



**Fig.15 Accuracy of the classifiers**

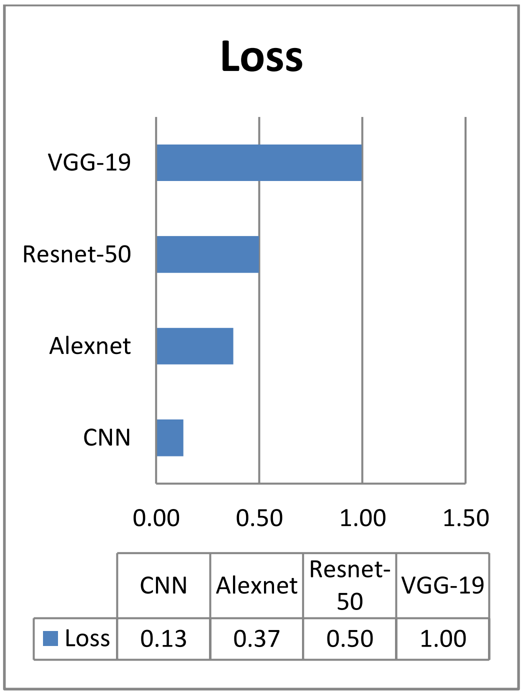



**Fig.16. Loss of the classifiers**

From the accuracy and loss graphs in Fig.15 and Fig.16, it is evident that the proposed CNN model has high accuracy and minimum loss value. The final classified output screenshots are shown in Fig.17. Labeled images are considered for testing so that the results can be evaluated accurately. It can display the images accurately along with the message box, it can be observed that the proposed model is able to classify correctly.


**Fig.17. Samples of final classified output – Labeled image along with "message box".**

**Conclusion**

1. In this work, thyroid nodule detection has been carried out by CNN and three different pre-trained networks, Alex net, Resnet-50 and VGG-19. The thyroid image is classified into six different classes. The proposed CNN model without the dropout layer is effective in classifying the images with an accuracy of 99.16%. While comparing the performance of the transfer learning techniques with the proposed CNN, the proposed CNN without the dropout layer performed well. The transfer learning architecture's, Alex net and ResNet are giving an average accuracy above 95%. This work also showcases the epoch versus time data, in which increasing the epochs has increased the time and the accuracy of the classification. The proposed method provides a better tool for the diagnosis of the stages of the thyroid nodule malignancy and thus helping physicians for improved diagnosis.

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