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# An Improved Deep Convolutional Neural Network Model for Thyroid Nodule Classification

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***Abstract*—Recently, Convolutional Neural Networks (CNNs) have become a methodology of choice for processing of medical images as they have a number of advantages compared to traditional machine learning techniques. In this paper, a deep Convolutional Neural Network for Thyroid Nodule Classification, CNN-TNC, is proposed using three different architectures to classify Thyroid Nodules using Thyroid Ultrasound (TUS) Images. Different data augmentation techniques like affine transformation that includes rotation, translation, scaling and shearing effects are carried out to increase TUS image dataset. At first, CNN-TNC is developed using custom architecture with 13-layer network which gave training accuracy of 79.65% and test accuracy of 72.50%. Further, to improve diagnostic accuracy of CNN-TNC, Transfer Learning (TL) technique is adopted using ResNet-18 and VGG-16 architectures. CNN-TNC implemented using ResNet-18 employing TL yielded train and test accuracy of 98.60% and 98.64% respectively. Also, CNN-TNC employing TL with VGG-16 resulted in an accuracy of 97.55% and 97% for train and test data respectively. CNN-TNC implemented using ResNet-18 and VGG-16 employing TL technique found to be the best when compared to CNN-TNC implemented with custom architecture. Obtained results demonstrate how fine-tuning pre-trained CNN models in a layer-wise method leads to incremental performance improvement when training data is limited.**

***Index Terms*— Convolution Neural Networks, Data Augmentation, Deep Learning, Image Processing, Thyroid Nodule, Transfer Learning.**

## I. INTRODUCTION

Deep Learning (DL), a promising machine learning approach has perceived immense amount of attention over the last few years for imaging applications. DL, also called deep neural network learning discovers complicated structure in large datasets by utilizing the backpropagation algorithm to specify how a computer modifies its internal parameters which are used to compute the representation in each layer using the representation of preceding layer [1]. Early neural networks were only a few layers deep, largely because the computing power was not sufficient for more layers and owing to challenges in updating the weights properly [2].

With fast improving computational power and the availability of enormous amounts of data, DL has become the default Machine Learning Technique (MLT) that is utilized since it can learn much more sophisticated patterns

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than conventional MLTs [3]. Unlike conventional MLTs, DL methods greatly simplify the feature engineering process and some have even been applied to raw data directly. This is especially important for the field of medical imaging analysis since it can take years of training to obtain adequate domain expertise for appropriate feature determination [4].

Among all DL methods, currently, the most popular architectures are CNNs. CNNs are the most successful type of models for image processing and analysis to date [5]. CNNs contain many layers that transform their input with convolution filters of a small extent. Compared to traditional MLTs, CNNs do not need computation of features and elimination of irrelevant features. Instead, CNN models, effectively finds important features as part of its search process. Along with the rapid increase of imaging data and hardware advancements in Graphical Processing Units (GPUs) have also led to improvements in CNN performance and their widespread use in medical image analysis.

In the present work, a deep neural network, CNN-TNC is designed using three different approaches to classify Thyroid Nodules (TNs) into benign and malignant by employing TUS images. Solid or fluid filled TNs are the lumps formed within the thyroid gland. Vast majority of TNs are benign, non-cancerous and do not cause symptoms. Benign nodules are very common in elderly population or people with iodine deficiency [6]. Small percentage (10%) of TNs are malignant meaning cancerous.

The paper frame work is as follows. Section II discusses the related research work carried out to classify TNs using deep learning techniques. The architecture of proposed CNN-TNC is explained in section III. Implementation details are explained in sections IV, V and VI. Experimental results are detailed in section VII followed by discussion and conclusion in sections VIII and IX respectively.

## II. Related Work

In recent years there is a tremendous interest in developing computer aided diagnosis systems using deep learning techniques for diagnosis of several diseases.

K V Sai Sundar et al., [7] made a comparative study of DL architectures to classify TNs using TUS images. They developed a custom architecture from scratch. Also, they applied transfer learning technique to develop CNN model by fine tuning INCEPTION-v3 and VGG-16. Further, later last layer of CNN was replaced with SVM. The performance of different architectures is carried out using accuracy, sensitivity and specificity. The combination of VGG-16 with SVM resulted in highest accuracy of 94%, sensitivity of 1.0 and specificity of 0.88 in contrast to accuracy of 82%, sensitivity of 0.82 and specificity of 0.89 obtained for custom designed CNN model. Through the results it was noted that good classification results were obtained when already existing DL architectures are fine tuned.

Vivian Y. Park et al., [8] developed an automated TN diagnosis system called DL-CAD employing DL concepts. DL-CAD consisted of segmentation stage where TN boundaries are extracted using semi-automated segmentation method. US features from extracted TNs are obtained using US-CAD software. Finally, TN boundary extracted image is given as input and extracted US image features are united in the feature layer of DL-CAD. The diagnostic results of DL-CAD are compared with SVM based CAD system and radiologist output. Results of DL-CAD were in line with radiologist output when compared with SVM based CAD system results.

Hailiang Li et al., [9] examined different schemes to enhance the capability of Faster R-CNN for spotting of thyroid Cancer Region (CR) in TUS images. Since US images have low resolution, blurred and moreover CRs are irregular in shape with unclear boundary training original CNN will not yield satisfactory results. To enhance the correct and complete spotting of CRs from TUS images spatial constrained layer to CNN is added (scheme 1). Along with this, shallow and deep layers of CNN are concatenated (scheme 2). Through the experiments it was observed that each scheme enhanced spotting of CR. Combination of both schemes gave best results i.e 93.5% of CRs were spotted automatically.

Xiangchun Li et al.,[10] did a prospective study of thyroid cancer US images and implemented DL model. The model DL-CNN was developed for automatic diagnosis of thyroid cancer using clinical TUS images. Training of DL-CNN was carried using huge image dataset of more than 300000 TUS images. Performance of developed DL-CNN model is verified with group of 16 different radiologists' findings. Initially ResNet model with 50 layers and Darknet model with 19 layers were trained and used for classifying cancer patients. Later an ensemble model combining the above two DL models was developed and performance of all three models were recorded. Through experiments authors concluded that ensemble model results were matching with radiologists' findings.

Yunjun Wang et al., [11] explored CNNs for classification of TNs using histopathology images. The images were augmented and separated into test and training set in the ration of 1:5. Transfer learning technique was employed to pretrained VGG-19-DL and Inception-Resnet-v2-DL models. These models were trained and tested using test and train datasets. VGG-19-DL model generated an improved accuracy of 97.34% than Inception-Resnet-v2-DL model (94.43%).

Liyong Ma et al., [12] implemented a DL model using SPECT images for thyroid diagnosis. The image dataset is augmented using mixup method. The current DL model DenseNet is upgraded with new architecture and training method. Modification to existing architecture is done with addition of trainable weight parameters to each skip connection and learning rate is optimized during training using flower pollination algorithm. Through experiment it was demonstrated that implemented DL CNN model is effective to diagnose different thyroid disorders with higher performance in comparison to other CNN techniques.

Xiaowen Liang et al., [13] to optimize cost ratio, developed a CNN model to diagnose both thyroid and breast nodules with comparable diagnostic features using US images. The original dataset was divided into four groups and four CNN models were built. Group1 consisted of images based on disease nature and group2 consisted of images based on disease type. Group1 and Group2 consisted of non-segmented images(original). Similarly, Group3 and Group4 consisted of segmented images. Through the experiment it was observed that CNN performance using segmented images was better than with non-segmented images. The results were also verified with radiologist and results of CNN models using segmented images (Group3 and 4) were superior to radiologist results.

## III. PROPOSED CNN-TNC

The proposed CNN-TNC is built using Pytorch [14], which is a DL framework that offers support for implementation of MLTs. An open-source tool Jupyter notebook is used to create application. Figure 1 shows the architecture of proposed CNN-TNC.

### *A. Image Collection*

Thyroid Ultrasound is the optimal initial imaging method in the screening of TNs due to its high resolution, low cost, availability, non-invasivity and no radiation load [15]. Ultrasound (US) is highly sensitive for detection of TNs and features like size, shape, location, composition, echogenicity, margins and vascularity of nodules obtained can be used for further investigation [16]. Ultrasound images containing benign and malignant TNs are used in the present study to design and test developed system. Both online and clinical nodular Thyroid Ultrasound (TUS) Images are used to carry out the experiment. The images were procured from radiology department of NRR hospital, Bangalore. A total of 200 images (150 benign, 50 malignant) are considered in this study. Along with these images an open access database of thyroid US images containing benign and malignant nodules are also used [17]. A total of 150 images (100 benign, 50 malignant) are considered in this study.

### *B. Data Augmentation (DA)*

DA is the method of increasing the volume and variety of data which is an integral process in DL. DA is one of the methods to overcome the problem of overfitting where the CNN model performed well for training data when compared to validation data. DL models require large amounts of data and in some cases huge data is not available, DA operation is performed [18]. In this method, no new data is gathered, instead the existing data is altered. For our TN image data set we have used different DA techniques like affine transformation that includes rotation, translation, scaling and shearing effects. Each of these techniques is applied to all the images of our thyroid image dataset. Some of the samples of the dataset after augmentation is shown in figure 2.

## IV. IMPLEMENTATION OF CNN-TNC USING CUSTOM ARCHITECTURE

CNN-TNC is developed using custom architecture with 13-layer network (Table I). In each Convolution Layer (CL), combination of 3 X 3 and 1 X 1 convolution filter with one padding and one stride is used. In the Max Pool (MP) layer kernel size and stride of 2 X 2 are used. Training of CNN-TNC was done using Cross Entropy (CE) loss function, Stochastic Gradient Descent (SGD) optimizer and a learning rate of 0.001 with decaying step of 7. Softmax Logistic Function (SLF) at Fully Connected Layer (FCL) is used for classification.

## V. VGG-16 WITH TRANSFER LEARNING (TL)

TL is a MLT that concentrates on storing knowledge obtained during solving a task and applying the stored knowledge to a new but related task [19]. For instance, knowledge attained during learning to identify different types of cars can be applied to identify trucks.

VGG-16[20] is a 16-layer CNN where 3x3 kernel in each CL, 2x2 kernel and stride 2 in MP layer is used. Softmax Activation Function (AF) is used in FCL for the classification. This network architecture is trained employing ImageNet dataset [21] which contains 14 million images of one thousand classes. For this model final FCL is modified with custom FCL of two classes. SLF is used for classification, SGD is used as an optimizer and loss function Binary CE with learning rate of 0.01 with decaying every seven steps is considered to modify VGG-16 model (Table II).

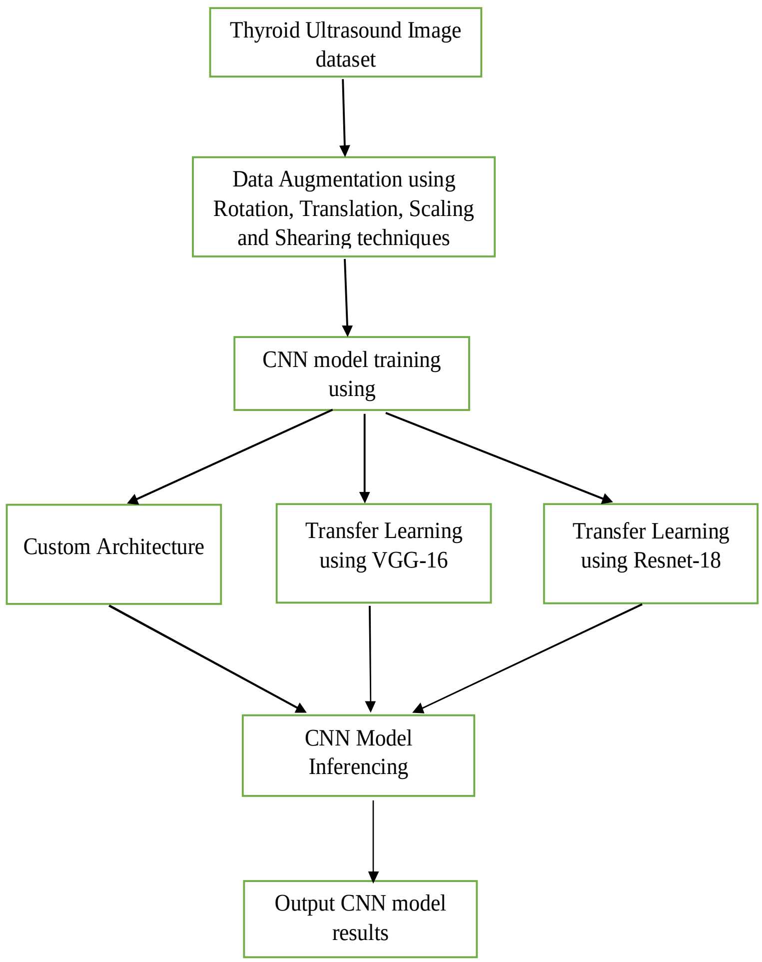
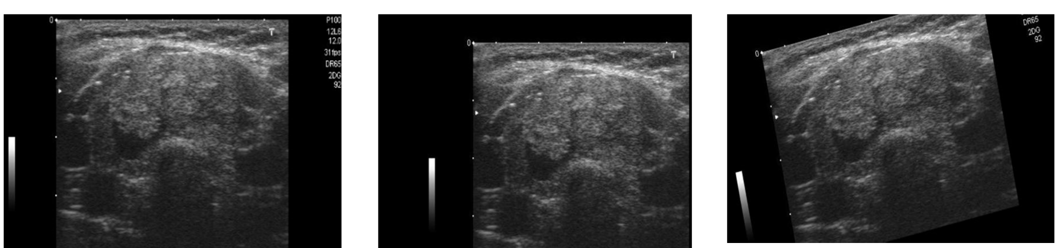
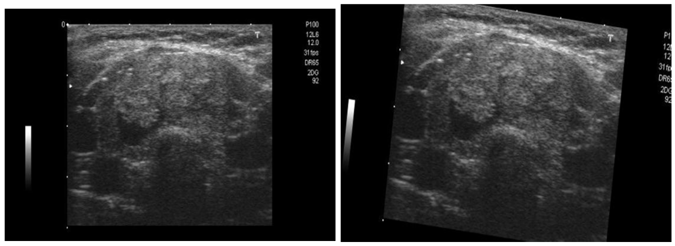



Figure 1: Architecture of proposed CNN-TNC



(a) TUS image (b) Translated image (c) Rotated image



(d) Scaled image (e) Sheared image

Figure 2: Augmented images

TABLE I: CNN-TNC CUSTOM ARCHITECTURE

| Layer | | Feature Map | Size | Kernel Size | Stride | Activation |
|---|---|---|---|---|---|---|
| Input | Image | 1 | 224 X 224 X 3 | - | - | - |
| 1 | 1XConvolution | 32 | 224 X 224 X 32 | 3X3 | 1 | Relu |
| 2 | 1XConvolution | 10 | 224 X 224 X 10 | 1X1 | 1 | Relu |
| 3 | Max Pooling | 10 | 112 X 112 X 10 | 2X2 | 2 | Relu |
| 4 | 1XConvolution | 64 | 112 X 112 X 64 | 3X3 | 1 | Relu |
| 5 | 1XConvolution | 10 | 112 X 112 X 10 | 1X1 | 1 | Relu |
| 6 | Max Pooling | 10 | 56 X 56 X 10 | 2X2 | 2 | Relu |
| 7 | 1XConvolution | 64 | 56 X 56 X 64 | 3X3 | 1 | Relu |
| 8 | 1XConvolution | 10 | 56 X 56 X 10 | 1X1 | 1 | Relu |
| 9 | 1XConvolution | 128 | 56 X 56 X 128 | 3X3 | 1 | Relu |
| 10 | 1XConvolution | 10 | 56 X 56 X 10 | 1X1 | 1 | Relu |
| 11 | Max Pooling | 10 | 28 X 28 X 10 | 2X2 | 2 | Relu |
| 12 | 1XConvolution | 256 | 28 X 28 X 256 | 3X3 | 1 | Relu |
| 13 | 1XConvolution | 16 | 28 X 28 X 16 | 1X1 | 1 | Relu |
| 14 | 1XConvolution | 256 | 28 X 28 X 256 | 3X3 | 1 | Relu |
| 15 | 1XConvolution | 16 | 28 X 28 X 16 | 1X1 | 1 | Relu |
| 16 | Max Pooling | 16 | 14 X 14 X 16 | 2X2 | 2 | Relu |
| 17 | 1XConvolution | 256 | 14 X 14 X 256 | 3X3 | 1 | Relu |
| 18 | 1XConvolution | 16 | 14 X 14 X 16 | 1X1 | 1 | Relu |
| 19 | 1XConvolution | 512 | 14 X 14 X 512 | 3X3 | 1 | Relu |
| 20 | FCL | | 100352 | | | Relu |
| Output | FCL | | 2 | | | Softmax |

Table II: CNN-TNC architecture using VGG-16 with TL

| Layer | | Feature Map | Size | Kernel Size | Stride | Activation |
|---|---|---|---|---|---|---|
| Input | Image | 1 | 224 X 224 X 3 | - | - | - |
| 1 | 2XConvolution | 64 | 224 X 224 X 64 | 3X3 | 1 | Relu |
| | Max Pooling | 64 | 112 X112 X 64 | 3X3 | 2 | Relu |
| 3 | 2XConvolution | 128 | 112 X 112 X 128 | 3X3 | 1 | Relu |
| | Max Pooling | 128 | 56 X 56 X 128 | 3X3 | 2 | Relu |
| 5 | 2XConvolution | 256 | 56 X 56 X 256 | 3X3 | 1 | Relu |
| | Max Pooling | 256 | 28 X 28 X 256 | 3X3 | 2 | Relu |
| 7 | 3XConvolution | 512 | 28 X 28 X 512 | 3X3 | 1 | Relu |
| | Max Pooling | 512 | 14 X 14 X 512 | 3X3 | 2 | Relu |
| 10 | 3XConvolution | 512 | 14 X 14 X 512 | 3X3 | 1 | Relu |
| | Max Pooling | 512 | 7 X 7 X 512 | 3X3 | 2 | Relu |
| 13 | FCL | - | 25088 | - | - | Relu |
| 14 | FCL | - | 4096 | - | - | Relu |
| 15 | FCL | - | 4096 | - | - | Relu |
| Output | FCL | - | 2 | - | - | Softmax |

## VI. IMPLEMENTATION OF CNN-TNC USING RESNET-18 ARCHITECTURE WITH TL

ResNet-18[22] is quite efficient because of its special residual function (skip connection) and is pretrained using ImageNet dataset [21]. The pre-trained model is used for our thyroid dataset with alteration in final layer. The FCL is altered with custom classification layer of two classes. SLF is used for classification, SGD is used as an optimizer and loss function Binary CE with learning rate of 0.01 with decaying every seven steps is considered to train ResNet-18 model (Table III).

TABLE III. CNN-TNC ARCHITECTURE USING RESNET18 WITH TL

| **Layer** | **Output Size** | **Resnet-18** |
|---|---|---|
| conv1 | 112 X112 X 64 | 7X7, 64, stride 2 |
| Conv2_x | 56 X 56 X 64 | 3X3 max pool, stride 2<br>$\begin{bmatrix} 3\,X3, 64 \\ 3X3, 64 \end{bmatrix} X\ 2$ |
| Conv3_x | 28 X 28 X 128 | 3X3 max pool, stride 2<br>$\begin{bmatrix} 3\,X3, 128 \\ 3X3, 128 \end{bmatrix} X\ 2$ |
| Conv4_x | 14 X 14 X 256 | 3X3 max pool, stride 2<br>$\begin{bmatrix} 3\,X3, 256 \\ 3X3, 256 \end{bmatrix} X\ 2$ |
| Conv5_x | 7 X 7 X 512 | 3X3 max pool, stride 2<br>$\begin{bmatrix} 3\,X3, 512 \\ 3X3, 512 \end{bmatrix} X\ 2$ |
| average pool | 1 X 1 X 512 | 7 X 7 average pool |
| fully connected | 2 | 512 X 2 full connections |
| Softmax | 2 | |

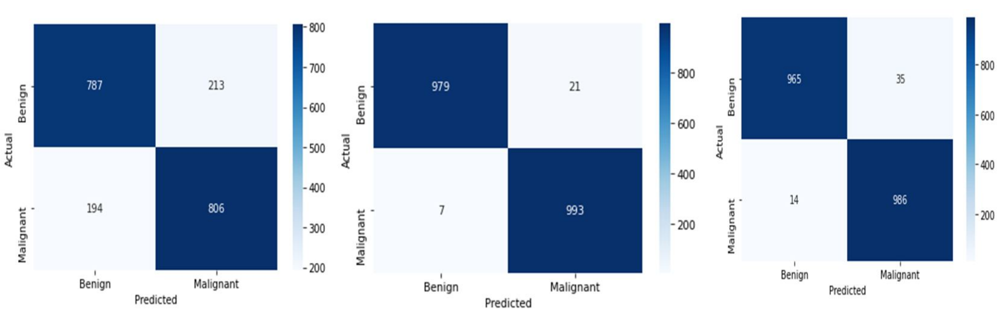
## VII. EXPERIMENTAL RESULTS

All the above DL architectures are trained using google Collab [23] which is GPU enabled. We have tried with many different sets of parameters and hyper parameters to tune the model and finally we got a better set of hyper parameters with better accuracy and generalization. Table IV shows the CNN-TNC model results for all three architectures carried for TN image dataset.

TABLE IV: CNN-TNC MODEL RESULTS USING THREE ARCHITECTURES

| **Model type** | **Accuracy** | | **Precision** | | **Recall** | | **F1 Score** | |
|---|---|---|---|---|---|---|---|---|
| | **Train** | **Test** | **Train** | **Test** | **Train** | **Test** | **Train** | **Test** |
| Trained on Custom Architecture | 79.65 | 72.50 | 0.79 | 0.71 | 0.81 | 0.72 | 0.79 | 0.72 |
| Trained using ResNet-18 with TL | 98.60 | 98.64 | 0.98 | 0.98 | 0.99 | 0.98 | 0.98 | 0.98 |
| Trained using VGG-16 with TL | 97.55 | 97.00 | 0.98 | 0.97 | 0.98 | 0.97 | 0.98 | 0.97 |

The corresponding confusion matrix (CM) of all three architectures is given in figure 3.




(i) (ii) (iii)

Figure 3: CM of (i) custom architecture (ii) ResNet-18, (iii) VGG-16

## VIII. Discussion

In the present paper the state-of-the-art DL model, CNN-TNC is developed to classify TNs using three different architectures. The performances of three architectures are compared in terms of train and test accuracy, precision, recall and F1-Score. Through the experimental it was noted that CNN-TNC implemented using custom architecture gave training accuracy of 79.65% and test accuracy of 72.50%. Since the size of our TUS image dataset after augmentation is 2200 images and DL models require massive data for training, we adopted TL technique using VGG-16 and ResNet-18 architectures. CNN-TNC implemented using both VGG-16 and ResNet-18 architectures employing TL concept boosted the classification results. The developed CNN-TNC yielded accuracy of 98.60% and 98.64%, precision value of 0.98 and 0.98, recall value of 0.99 and 0.98 and f-score of 0.98 and 0.98 for train and test data respectively employing TL technique using ResNet-18 architecture. Further, CNN-TNC employing TL with VGG-16 yielded accuracy of 97.55% and 97%, precision value of 0.98, recall value of 0.98 and f-score of 0.98 for train and test data respectively. Obtained results demonstrate how fine-tuning pre-trained DL models in a layer-wise method leads to incremental performance improvement when training data is limited. Sample output of CNN-TNC using three architectures is shown in figures 4,5 and 6. CNN-TNC implemented using ResNet-18 resulted in a highest accuracy of 98.64% compared to our earlier two systems developed using MLTs and fuzzy concepts as shown in figure 7 [24, 25].

## IX. Conclusion

Traditional MLTs require much time and effort to extract and select best features from medical images. DL techniques, notably CNNs proved its potential with finest results on different image classification tasks. The purpose of this work is to develop an automated TN diagnosis system using DL that could support the radiologist by shortening examination time there by reducing his examination load. The developed CNN-TNC yielded accuracy of 98.60% and 98.64%, precision value of 0.98 and 0.98, recall value of 0.99 and 0.98 and f-score of 0.98 and 0.98 for train and test data respectively employing TL technique using Resnet-18 architecture. Further, CNN-TNC employing TL with VGG-16 yielded accuracy of 97.55% and 97%, precision value of 0.98, recall value of 0.98 and f-score of 0.98 for train and test data respectively. The present work demonstrated that TL has the potential to improve diagnostic accuracy of CNN model when the dataset is not large. It also demonstrated that instead of training CNN from scratch one can make use of pre-trained DL models with adequate fine tuning to improve the performance. The DL models proved to be better when compared to traditional MLTs as shown in Figure 7. In addition, it was also observed that the overall average accuracy of fuzzy inference model was almost same as DL model.

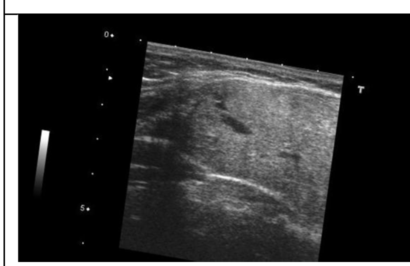
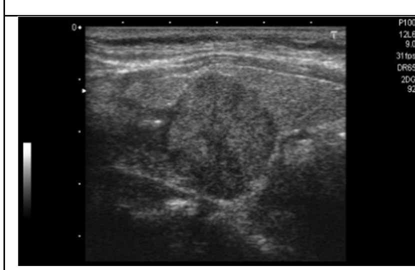
| **TUS image** | **Ground Truth** | **Custom Model Result** |
|---|---|---|
|  | **Benign** | **Malignant** |
|  | **Malignant** | **Malignant** |

Figure 4: Sample output of CNN-TNC using custom architectures

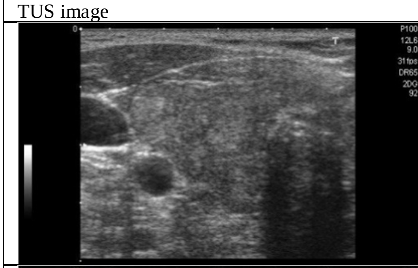
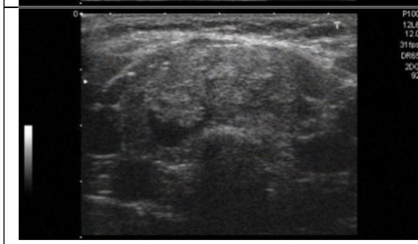
| TUS image | Ground Truth | Resnet-18 model Result |
|---|---|---|
|  | Benign | Malignant |
|  | Benign | Malignant |

Figure 5: Sample output of CNN-TNC using Resnet-18 architecture

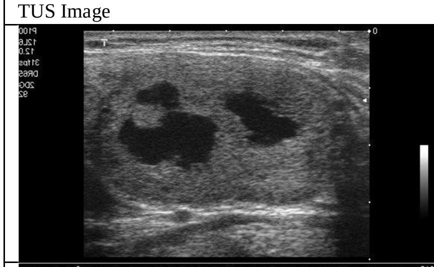
| TUS Image | Ground truth | VGG-16 Model result |
|---|---|---|
|  | Benign | Malignant |
|  | Benign | Benign |

Figure 6: Sample output of CNN-TNC using VGG-16 architecture

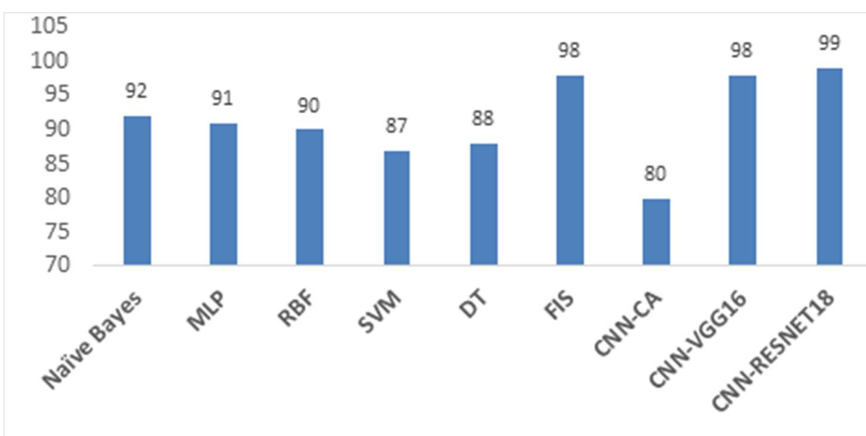



Figure 7. Comparative performance of traditional MLTs, FIS and DL architectures classifiers for TN diagnosis

REFERENCES


[1] Yann LeCun, Y. Bengio, Geoffrey Hinton, "Deep Learning", Nature, Vol. 521, pp. 436-444, 2015

[2] Hesamian M.H., Jia W, He X, Kennedy P, "Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges", Journal of Digit Imaging, Vol. 32, pp. 582–596, 2019

[3] Lakhani P, Gary D, Pett C, Nagy P, "Hello World Deep Learning in Medical Imaging", Journal of Digital Imaging, Vol. 31, pp. 283-289, 2018

[4] Dutta S, Manideep CS, Rai S, Vijayan V, "A Comparative Study of Deep Learning Models for Medical Image Classification", IOP Conference Series: Materials Science and Engineering, Vol. 263, 2017

[5] Litjens G, Kooi T, Bejnordi B E, Setio A A A, Ciompi F, Ghafoorian M, Laak J, Ginneken B V, Sanchez, "A Survey on Deep Learning in Medical Image Analysis", Medical Image Analysis, Vol. 42, pp. 60-88, 2017

[6] Victor J. Bernet, Ana-Maria Chindris, "Update on the Evaluation of Thyroid Nodules", Journal of Nuclear Medicine, Vol. 62, pp. 13S-19S, 2021

[7] K.V. Sai Sundar, K.T. Rajamani, S. Siva Sankara Sai, "Exploring Image Classification of Thyroid Ultrasound Images Using Deep Learning", Proceedings of the International Conference on ISMAC in Computational Vision and Bioengineering 2018, pp.1635-1641

[8] Vivian Y. Park, Kyunghwa Han, Yeong Kyeong Seong, Moon Ho Park, EunKyung Kim, Hee Jung Moon, Jung HyunYoon, JinYoung Kwak, "Diagnosis of Thyroid Nodules: Performance of a Deep Learning Convolutional Neural Network Model vs. Radiologists", Scientific Reports, Natureresearch, Vol. 09, No. 01, 2019

[9] Hailiang Li, Jian Weng, Yujian Shi, Wanrong Gu, Yijun Mao, Yonghua Wang, Weiwei Liu, Jiajie Zhang, "An improved deep learning approach for detection of thyroid papillary cancer in ultrasound images", Scientific Reports, 2018

[10] Xiangchun Li, S Zhang, Q Zhang, Xi Wei, Yi Pan, J Zhao, X Xin, C Qin, X Wang, J Li, F Yang, Y Zhao, M Yang, Q Wang, Z Zheng, X Zheng, X Yang, C T Whitlow, M N Gurcan, "Diagnosis of thyroid cancer using deep convolutional neural network models applied to sonographic images: a retrospective, multicohort, diagnostic study", Lancet Oncol, Vol, 20, pp. 193-201, 2019

[11] Y Wang, Q Guan, I Lao, L Wang, Y Wu, D Li, Q Ji, Y Wang, Y Zhu, H Lu, J Xiang, "Using deep convolutional neural networks for multi-classification of thyroid tumor by histopathology: a large-scale pilot study", Annals of Translational Medicine, Vol. 07, No. 18, 2019

[12] Liyong Ma, Chengkuan Ma, Yuejun Liu, Xuguang Wang, "Thyroid Diagnosis from SPECT Images Using Convolutional Neural Network with Optimization", Hindawi Computational Intelligence and Neuroscience, 2019

[13] Xiaowen Liang, Jinsui Yu, Jianyi Liao, Zhiyi Chen, "Convolutional Neural Network for Breast and Thyroid Nodules Diagnosis in Ultrasound Imaging", Hindawi BioMed Research International, 2020

[14] Pytorch.org/tutorials/

[15] Manfred Blum, "Ultrasonography of the Thyroid", Endotext [Internet], https://www.ncbi.nlm.nih.gov/books/NBK/285555/

[16] Cheng Xie, Peter Cox, Nia Taylor, Sarah LaPorte, "Ultrasonography of Thyroid Nodules: A Pictorial Review", Insights Imaging, Vol. 07, No. 01, pp. 77-86, 2016

[17] Digital Database Thyroid Image. http://www.cimalab.unal.edu.co Date accessed 10/10/2021

[18] Shorten C, Khoshgoftaar T M, "A Survey on Image Data Augmentation for Deep Learning", Journal of Big Data, Vol. 60, 2019

[19] Hussain M, Bird J J, Faria D R, "A Study on CNN Transfer Learning for Image Classification", 18th Annual UK Workshop on Computational Intelligence, 2018

[20] Geeksforgeeks.org/vgg-16-cnn-model

[21] www.image-net.org

[22] towardsdatascience.com/an-overview-of-resnet-and-its-variants

[23] colab.research.google.com

[24] Poornima D, Asha Gowda Karegowda, "CFS based Feature Subset Selection for Enhancing Thyroid Nodule Classification- A Filter Approach", Third International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT) 14th-15th December 2018

[25] Poornima D, Asha Gowda Karegowda, Pushpalatha K. R, "Design of Fuzzy Inference based Ultrasound Image Analysis System for Differential Diagnosis of Thyroid Nodules", Third International Conference on Integrated Intelligent Computing, Communication and Security (ICIIC-2021), 6th-7th August 2021