# Deep Learning for Classification of Benign and Malignant Thyroid Nodules in Ultrasound Imaging

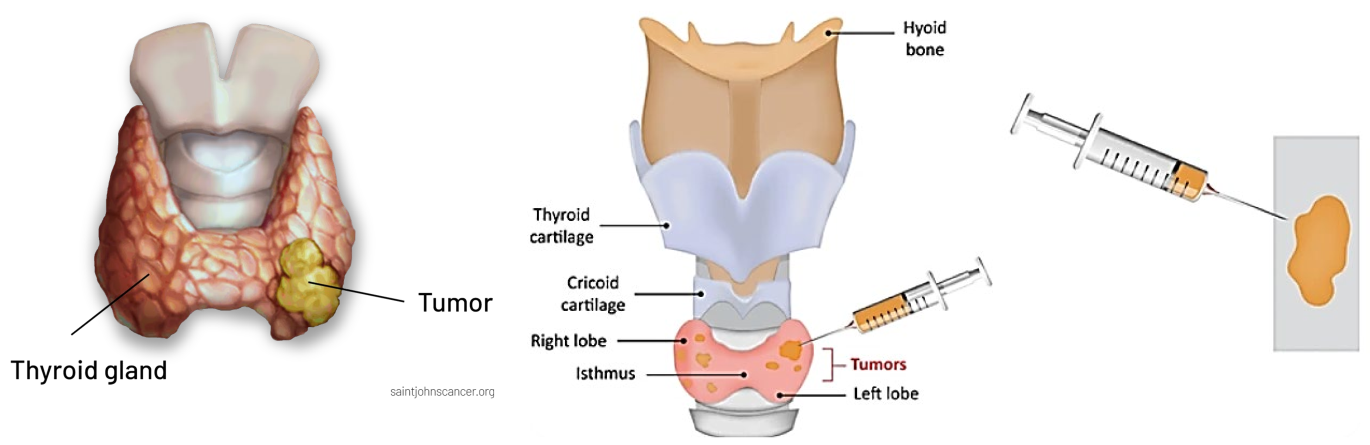
**Masiel Velarde[1], Manali Saini, Ph.D.[2], Azra Alizad, M.D.[2,3], Mostafa Fatemi, Ph.D.[3]**

[1]University of Texas at El Paso; [2]Department of Radiology, Mayo Clinic College of Medicine and Science, Rochester, MN; [3]Department of Physiology and Biomedical Engineering , Mayo Clinic College of Medicine and Science, Rochester, MN

## ABSTRACT

### Introduction

Thyroid nodules, characterized by abnormal cell growth within the thyroid gland, pose a significant diagnostic challenge due to the need to accurately distinguish between benign and malignant forms. This differentiation is crucial to prevent unnecessary fine needle aspiration (FNA) and surgical resection, which, despite being effective, are invasive and can cause patient discomfort and anxiety. The invasive nature of FNA, along with its associated risks and patient burden, underscores the need for non-invasive diagnostic alternatives that can provide accurate results without the associated drawbacks.




To address this need, this study introduces a deep learning framework which combines depth-wise separable convolutional layers and a squeeze-and-excite (SE) block to classify benign and malignant thyroid nodules. This framework leverages B-mode and shear wave elastography (SWE) ultrasound images, which are non-invasive imaging techniques, to analyze thyroid nodules.

## DATA

The dataset used in this study comprises thyroid gland images from 350 patients, including approximately 2000 benign and 1800 malignant nodules, providing a robust basis for validation. This involves:

•**Patient Data:** A sample size of 448 patients with an age range of 18-87 years and a mean age of 55.73 years.
•**Classification Basis:** Based on fine needle aspiration (FNA) pathology results for accurate sorting into benign and malignant categories.
•**Imaging Modes**: This study utilizes B-mode and SWE ultrasound Images. Figure 1 shows a selected benign and malignant case.

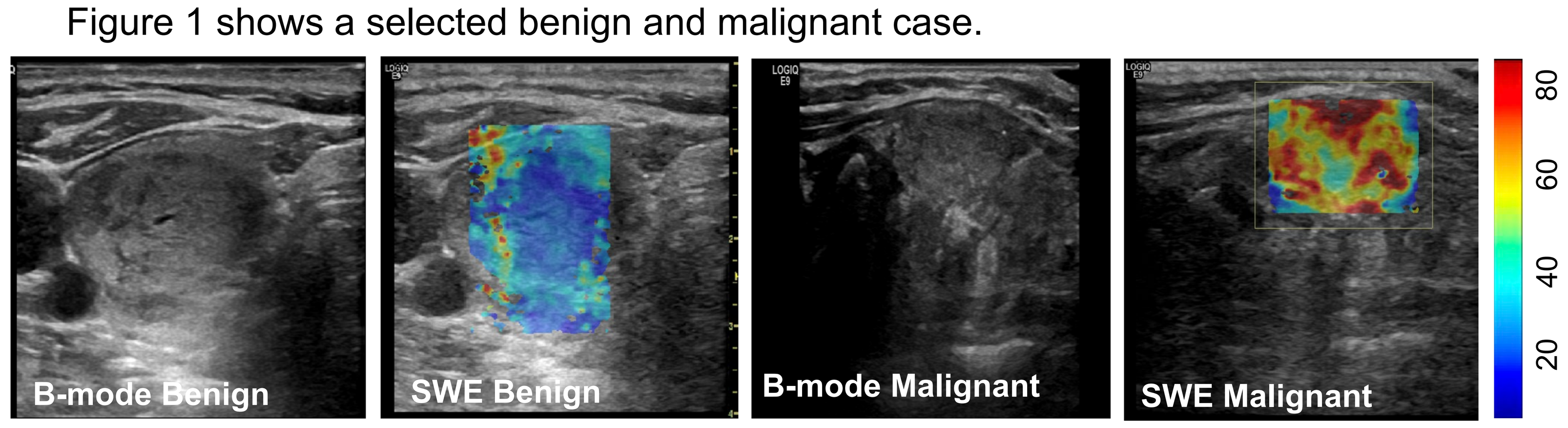



**Figure 1:** Ultrasound images of Shear Wave Elastography (SWE) and B-mode, classified as benign and malignant.

## METHOD

**Model Architecture**: The proposed model utilizes a custom architecture with SeparableConv2D layers, Batch Normalization, MaxPooling2D, AveragePooling2D, Dropout, Add, Flatten, Dense, Multiply, GlobalAveragePooling2D, Reshape layers, and a squeeze-and-excite attention block. The complete structure is presented in Figure 2.



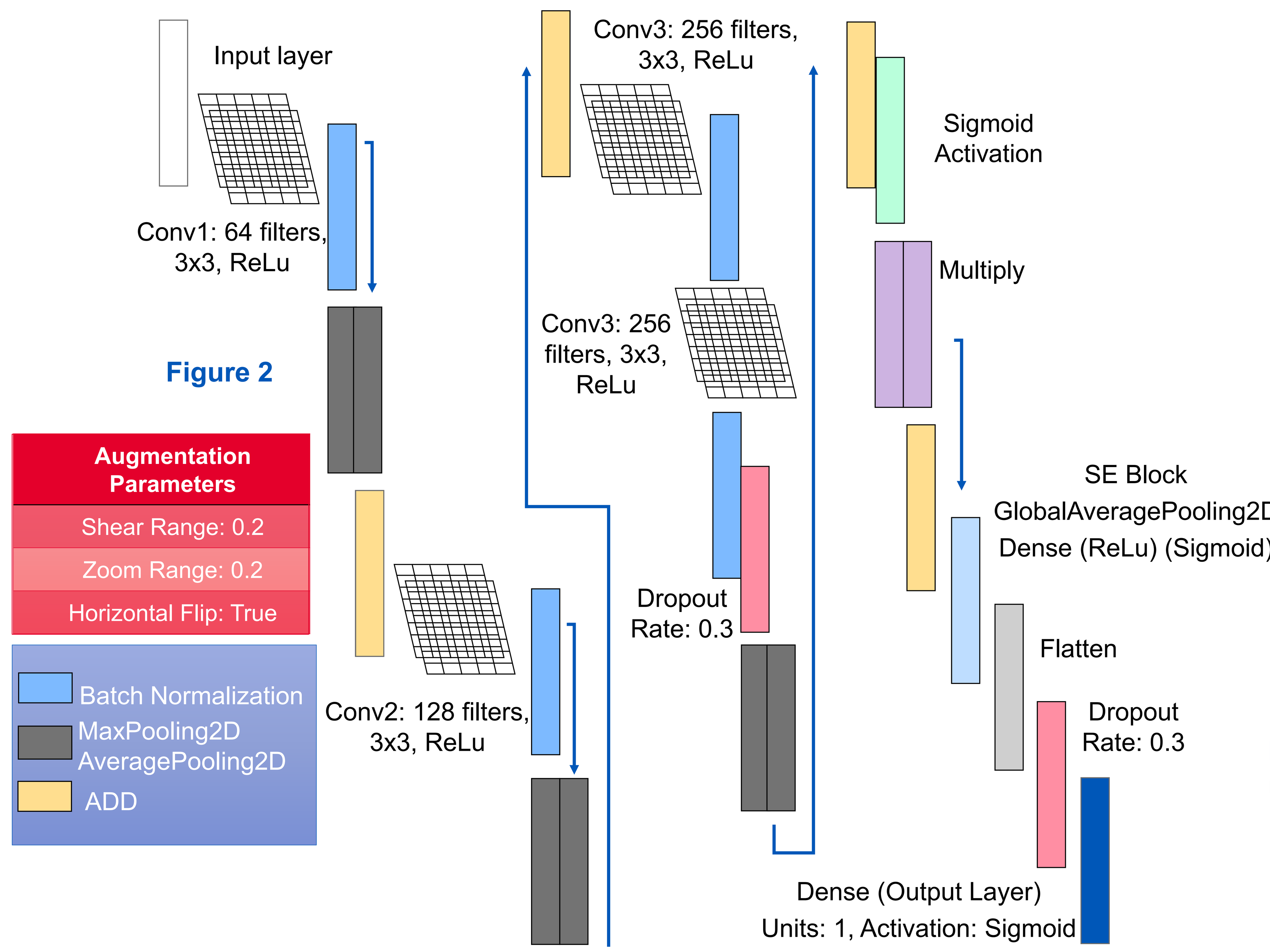



**Figure 2:** Proposed model architecture.

•**Data Split**: The data is split into 70% for training and 30% for testing. During training, 30% of the training data is further used for validation.
•**Loss Function**: Binary focal cross entropy with class balancing and a gamma value of 2 is used as the loss function.
•**Optimizer**: Adam optimizer with a learning rate of 0.00005 is used for training the model.
•**Training Parameters**: The model is trained for 250 epochs with a batch size of 16 and a verbose level of 2.

## RESULTS

To evaluate the performance of the proposed model different classification metrics are used for the test data. The performance assessment studies indicate that the proposed model achieved an average test accuracy of 0.95, F1-score of 0.91, and area under the receiver operating characteristics curve (AUROC) of 0.97. Figure 3 presents the AUROC and area under precision-recall curve (AUPRC) for demonstrating the model's classification performance.

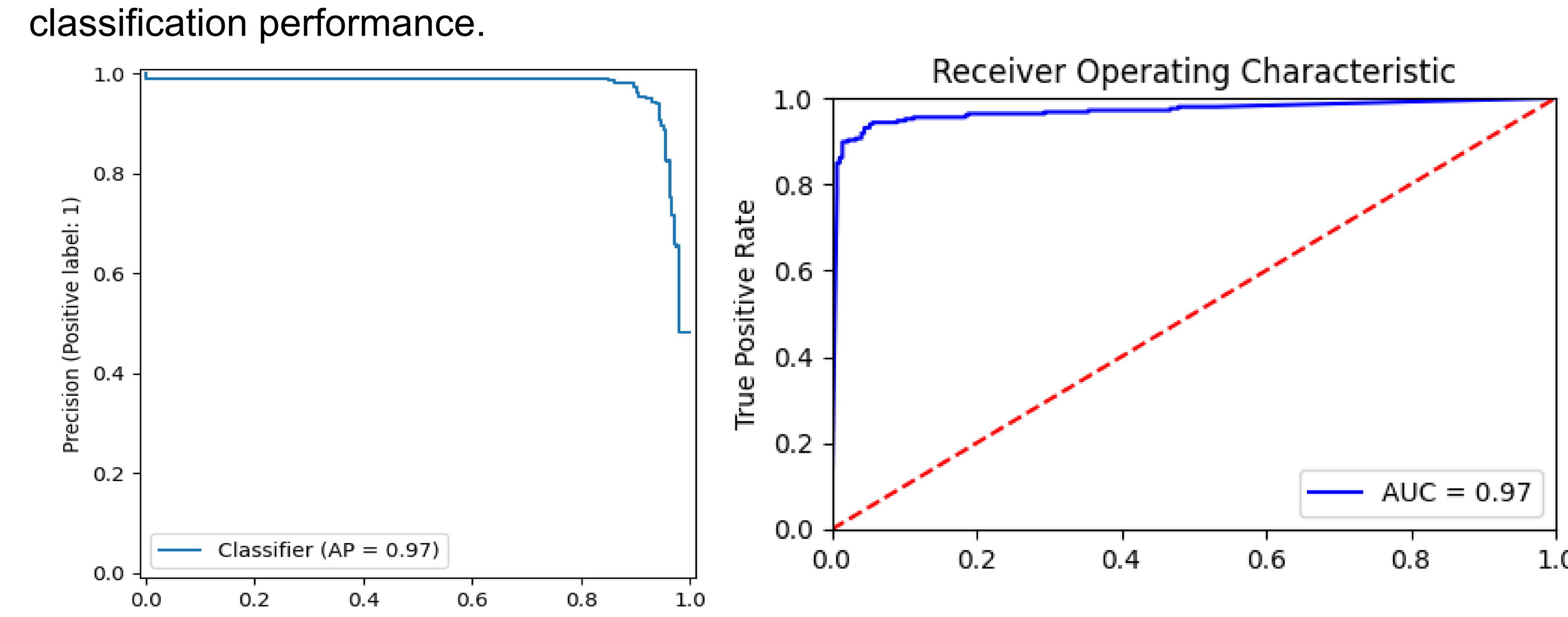



**Figure 3:** AUPRC of 0.97, reflecting optimal trade-off between the precision and recall and AUROC of 0.97, indicating the model's capability in distingiuishing the benign and malignant nodules.

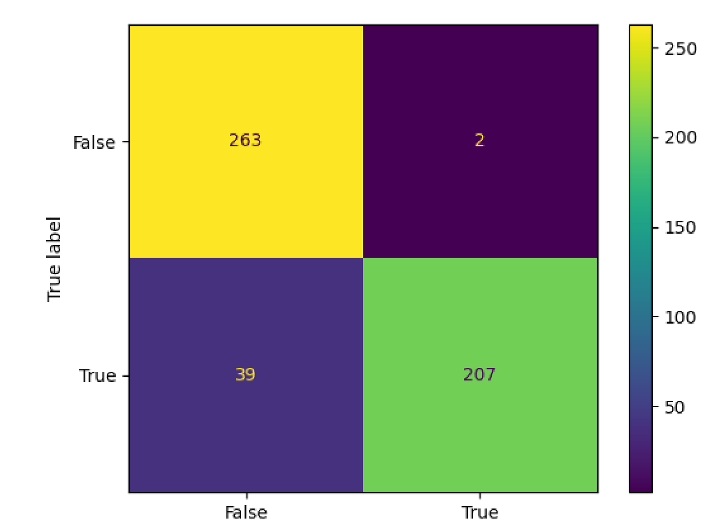



**Figure 4:** Confusion Matrix: High overall accuracy with minimal misclassifications, demonstrating effective classification of thyroid nodules.

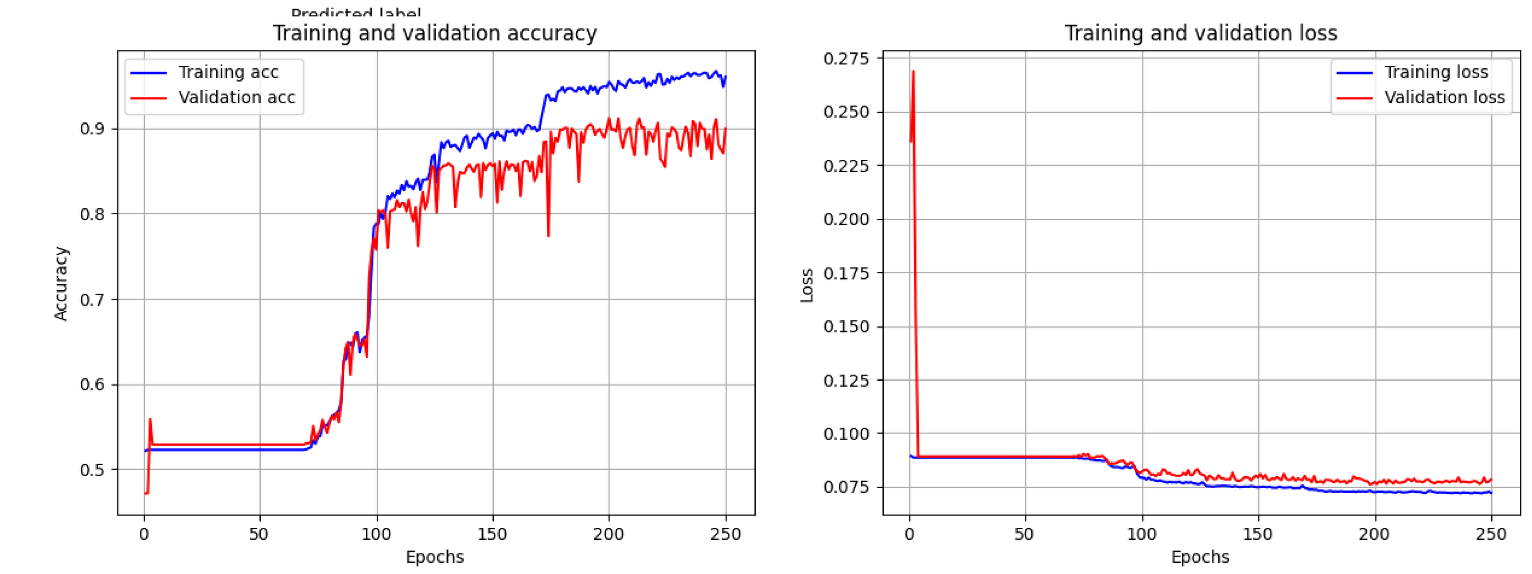



**Figure 5:** Left- Plot showing the training and validation accuracy over 250 epochs, with accuracy reaching 95%. Right- Plot demonstrating a significant reduction in loss to around 7%

| Mrthod | Test Accuracy | Precision | Recall | F1 | AUROC |
|---|---|---|---|---|---|
| *Proposed | 0.95 | 0.97 | 0.97 | 0.92 | 0.97 |
| ResNet18 | 0.94 | 0.97 | 0.93 | 0.96 | 0.97 |
| Incentive- V3 | 0.93 | 0.96 | 0.91 | 0.93 | 0.93 |

**Table 1:** Comparison of the proposed model with ResNet18 and Incentive-V3 across various performance metrics. The proposed model shows superior performance in most metrics.

## CONCLUSION

The proposed model is able to classify benign and malignant thyroid nodules using the bimodal images with a high accuracy. This demonstrates the effectiveness of the proposed framework in extracting discriminative features for differentiating between the benign and malignant nodules. Further comparative evaluation with the existing studies using the pre-trained models such as, ResNet-18 and Inception-v3 indicates its superiority in terms of performance as well as light-weight architecture.

Finally, these results underscore the efficacy of the proposed deep learning approach in providing accurate, and non-invasive diagnosis of thyroid nodules in real-time, thereby reducing the need for invasive procedures.

## FUTURE WORK

Future work will integrate additional imaging modalities like Doppler ultrasound and explore advanced neural network architectures to enhance classification accuracy. Testing the model on larger, diverse datasets will validate its generalizability. Further analysis may include implementing real-time image analysis and developing an automated diagnostic tool for clinical use.

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