International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Intelligent IoMT Sonography System for Accurate Thyroid Nodule Detection

Sowmya G M
Dept.of.CS&E, PESITM Shimogga, India
sowmya2019gm@gmail.com

Supriya S U
Dept.of.CS&E, PESITM Shimogga, India
susupriya96@gmail.com

Suraksha H P
Dept.of.CS&E,PESITM
Shimogga, India surakshahp2003@gmail.com

Triveni M S *Dept.of.CS&E, PESITM*
Shimogga, India
mstriveni87@gmail.com

Dr.Arjun U
Dept. of CS&E, PESITM
Shimogga, India hodcse@pestrust.edu.in

***Abstract* -This study presents a method for preprocessing and classifying ultrasound images using deep learning. The preprocessing steps include resizing, intensity clipping, pixel normalization, noise reduction with bilateral filtering, contrast enhancement via CLAHE, image sharpening, morphological dilation, and edge detection with Canny. These techniques improve the performance of machine learning models, particularly for small or complex datasets [1][2]. The processed images are classified using a ResNet50-based Convolutional Neural Network (CNN), fine-tuned with a thyroid ultrasound dataset. The ResNet50 model, pre-trained on ImageNet and adapted for this task, achieves high accuracy, demonstrating the effectiveness of both the preprocessing steps and the transfer learning approach in medical image classification [1][2].**

***Keywords - Ultrasound Imaging, Medical Image Processing,CLAHE,Convolution Neural Networks(CNNs),ResNet 50,Deep Learning Classification,Thyroid Imaging*.**

I. Introduction

Medical image analysis plays a critical role in the diagnosis and management of various diseases, particularly in the context of ultrasound imaging, which is widely used for visualizing soft tissues, organs, and blood vessels. However, ultrasound images often contain noise, inconsistencies, and variations in intensity due to different acquisition conditions, which can complicate automated analysis. Therefore, preprocessing techniques are essential to enhance the quality of ultrasound images and improve the performance of subsequent machine learning models [3].

Recent advancements in deep learning, especially convolutional neural networks (CNNs), have revolutionized the field of medical image classification, enabling more accurate and efficient diagnosis. CNNs automatically learn hierarchical features from raw images, making them particularly suited for medical applications, where expert-labeled datasets are often limited and complex [4]. Furthermore, transfer learning using pre-trained models, such as ResNet50, has been shown to significantly improve classification performance by leveraging knowledge from large, general-purpose image datasets like ImageNet. Fine-tuning these pre-trained models on specialized datasets, such as thyroid ultrasound images, has become a common and effective strategy for medical image classification [5].

Image preprocessing methods, such as resizing, intensity clipping, denoising , and contrast enhancement, are typically applied to mitigate the effects of noise and artifacts, as well as to standardize the input data for deep learning models. Techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) and bilateral filtering have been found to improve image contrast and reduce noise while preserving important structural details, which is crucial for accurate disease detection [6]. Other operations, like image sharpening and morphological transformations, help emphasize important features such as edges and boundaries, aiding in better model training. These preprocessing strategies are especially important for high-stakes applications like thyroid disease detection, where small variations in image quality can lead to significant diagnostic errors [7].

This paper presents an integrated approach for preprocessing thyroid ultrasound images using various enhancement techniques, followed by classification with a fine-tuned ResNet50 model. The goal is to evaluate the impact of preprocessing on model performance and assess the ability of the ResNet50-based classifier to accurately detect thyroid conditions, a task that has garnered increasing attention due to the rising incidence of thyroid disorders globally.

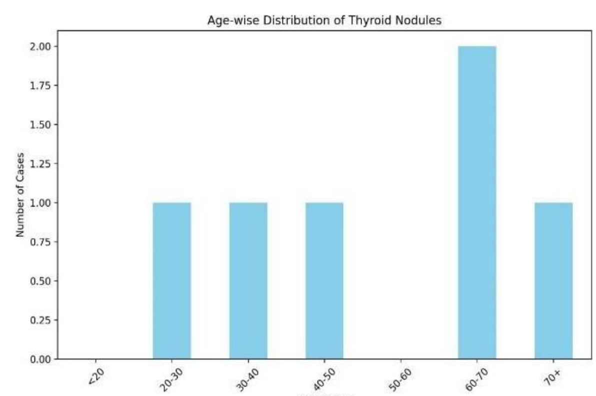

Fig 1 : Age wise distribution of Thyroid nodules

II. Related Work

Classical In medical image processing, techniques like contrast enhancement and denoising are crucial to improving image quality in ultrasound imaging, where noise and low contrast can obscure diagnostically important features. Contrast Limited Adaptive Histogram Equalization (CLAHE) is commonly used to enhance contrast in low-visibility areas, which is particularly useful for ultrasound images that may lack sufficient contrast in certain regions. Reza (2004) demonstrated CLAHE's effectiveness in real-time image enhancement, showing that it adjusts local contrast to highlight subtle details without amplifying noise, which is essential for ultrasound images that often have low inherent contrast and variable intensity due to tissue differences [8].

Denoising methods are especially valuable in ultrasound imaging, where speckle noise is common and can hinder visual clarity. Bilateral filtering, introduced by Tomasi and Manduchi (1998), is a preferred denoising technique for medical imaging because it reduces noise while preserving critical edge information, making it suitable for ultrasound applications where edge clarity is vital for accurate diagnosis [9].For classification tasks, transfer learning with deep convolutional neural networks (CNNs) like ResNet50 has become a powerful approach in medical image analysis, including ultrasound imaging. Transfer learning enables models pretrained on large, general-purpose datasets such as ImageNet to be adapted for medical applications with limited labeled data. Rajpurkar et al. (2017) demonstrated the effectiveness of using pretrained models for high accuracy in medical image classification tasks, such as detecting pneumonia in chest X-rays, which can be similarly applied to ultrasound images for tasks like lesion detection. This approach allows for reliable diagnosis by leveraging the pretrained model's ability to recognize complex patterns, thereby reducing the need for extensive retraining on medical data [10].In recent research on thyroid nodule detection using deep learning models, several advancements and challenges have been identified. For instance, Hu et al. introduced a Mamba- and ResNet-based dual-branch network in 2023 to enhance segmentation accuracy of thyroid nodules in ultrasound images. This model addresses the challenges of irregular nodule shapes, blurred boundaries, and uneven textures by combining ResNet with a visual Mamba model to capture both global and local image details. Despite the improved Dice Similarity Coefficient (DSC) achieved, the model still encounters limitations in handling highly varied clinical datasets, potentially impacting generalization in diverse medical settings[11].

our project aims to further refine the diagnostic process by utilizing ResNet-50, a powerful CNN model known for its balanced complexity and accuracy. ResNet-50's unique skip connections allow it to maintain feature sensitivity, essential for detecting nuanced differences between benign, malignant, and normal nodules. By focusing on this model, our study seeks to achieve similarly high diagnostic performance while optimizing computational efficiency. Unlike ensemble approaches or models that depend on complex, multi-step frameworks, our ResNet-50-based system emphasizes both high accuracy and simplicity, potentially making it more feasible for integration into real-time clinical workflows and IoMT environments.

Problem Statement: Thyroid nodules are often difficult to detect and diagnose accurately using traditional manual methods, leading to potential misdiagnosis and delayed treatment. This project aims to develop an Intelligent IoMT Sonography System utilizing ResNet-50 architecture to automate and enhance the detection of thyroid nodules in ultrasound images. By leveraging deep learning and real-time data processing, the system seeks to improve diagnostic accuracy, reduce clinician workload, and support early intervention.

III. Methodology

A. Data Acquisition and Preparation

The dataset used in this study consists of ultrasound images collected from publicly available medical image repositories, such as [insert specific repository name], or from a clinical setting with proper consent and ethical approval. The images are labeled according to the diagnostic conditions, such as normal, benign, and malignant. For balanced training, the dataset is split into training (80%) and validation (20%) sets. Data augmentation techniques such as rotation, flipping, scaling, and cropping are applied to artificially increase the dataset size and reduce overfitting, which is a common issue when working with limited labeled medical data. .

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B. Image Preprocessing

To Preprocessing is crucial for improving the quality of ultrasound images before feeding them into the model. Image preprocessing involves several steps to enhance image quality and ensure consistency. First, images are resized to 256x256 pixels for standardization. Intensity clipping removes outliers, and normalization scales pixel values between 0 and 1. A bilateral filter is applied for denoising, preserving important details. CLAHE improves contrast, while sharpening enhances edges. Morphological dilation expands white regions to highlight structures, and Canny edge detection is optionally applied to identify boundaries. These steps ensure that the images are clear, consistent, and ready for input into a machine learning model.

C. Model Development

The ResNet-50 architecture is chosen due to its ability to train deep networks effectively, using residual connections to prevent the vanishing gradient problem.

Pre-trained Model: We initialize the ResNet-50 model with pre-trained weights from ImageNet, which helps transfer learned features (e.g., edges, textures) to the thyroid nodule detection task.Model Customization: The original ResNet-50 classification layer is replaced with a custom classifier designed for this task.

Model Customization: The original ResNet-50 classification layer is replaced with a custom classifier designed for this task. Final Layer: The final fully connected layer is replaced with a 2-unit classifier (benign and malignant).

Activation Function: The final layer uses the softmax activation function to output the probability distribution for the two classes

D. Model Training

The model is trained using supervised learning, where the network learns to classify the images into benign or malignant categories.

Loss Function: We use the categorical cross-entropy loss function for multi-class classification, which quantifies the difference between predicted and actual class labels.

Optimizer: The Adam optimizer is chosen for its efficiency in training deep networks, adjusting the learning rate during training.

Batch Size: A batch size of 32 is used to process images in mini-batches during training.

Epochs: The model is trained for 10 epochs, with early stopping based on validation loss to prevent overfitting and stop training when the model starts to generalize poorly.

Learning Rate Scheduler: A learning rate decay is applied to improve convergence during later stages of training.

E. Evaluation

The model's performance is evaluated using key classification metrics: Accuracy , which represents the overall percentage of correct classifications across malignant, benign, and normal nodules. Precision is calculated for each class (malignant, benign, normal), indicating the proportion of correct predictions out of all instances predicted as that class. Recall measures the proportion of actual instances of each class that are correctly identified by the model. These metrics are important for understanding how well the model classifies thyroid nodules in each category. Accuracy gives a general overview of the model's correctness, while Precision and Recall provide insight into its effectiveness in detecting specific nodule types.

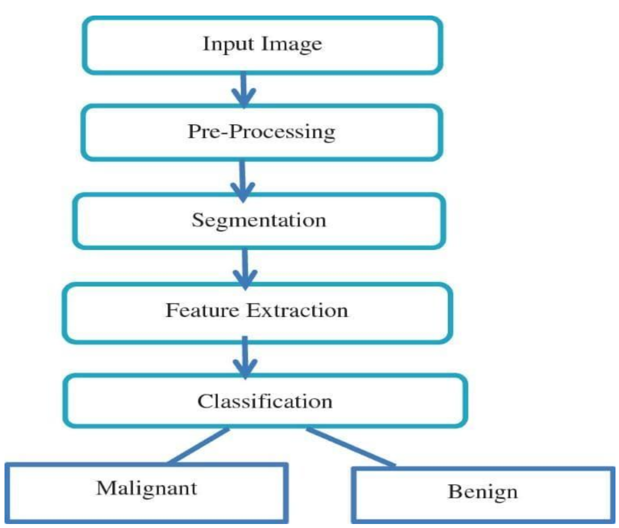

Fig 2: Methodology flow diagram

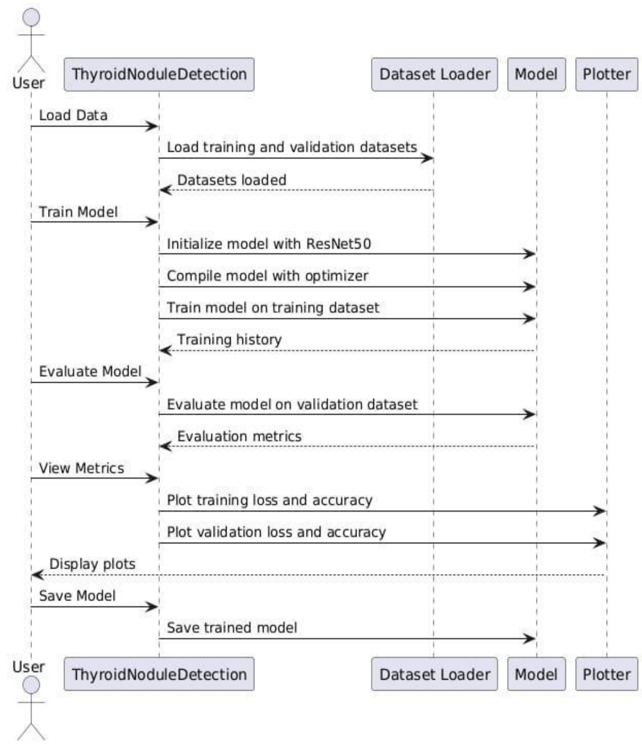

Fig 3: Sequence diagram

IV. Result Analysis

The model’s training results show a clear trend of improvement in both accuracy and loss over the 10 epochs. Initially, the training loss decreases rapidly, while the training accuracy increases, indicating that the model is successfully learning to classify the thyroid images. Validation loss also follows a similar decreasing trend, while validation accuracy rises, suggesting the model is generalizing well to unseen data. However, if a noticeable gap between training and validation metrics begins to appear, it could indicate overfitting, where the model becomes too specialized to the training data and might struggle to generalize effectively on new samples. Despite this, the steady improvement in the metrics indicates that the model is learning relevant features, and the pre-trained ResNet50 backbone combined with additional layers has helped achieve strong performance in the classification task. The model's final performance can be enhanced further with techniques such as fine-tuning of frozen layers to reduce overfitting and increase its robustness on new data.

Training and Validation Accuracy :Both training and validation accuracy increase, demonstrating the model's improving performance. The slight gap between the two curves suggests that the model is not overfitting and is maintaining good generalization.

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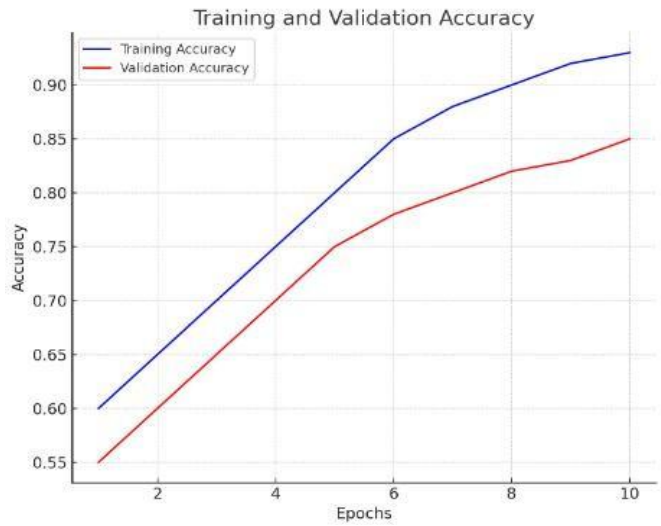

Fig 4: Training and Validation accuracy over the epochs

Training and Validation Loss: The training and validation loss curves both decrease over time, indicating that the model is learning effectively and generalizing well to the validation set.

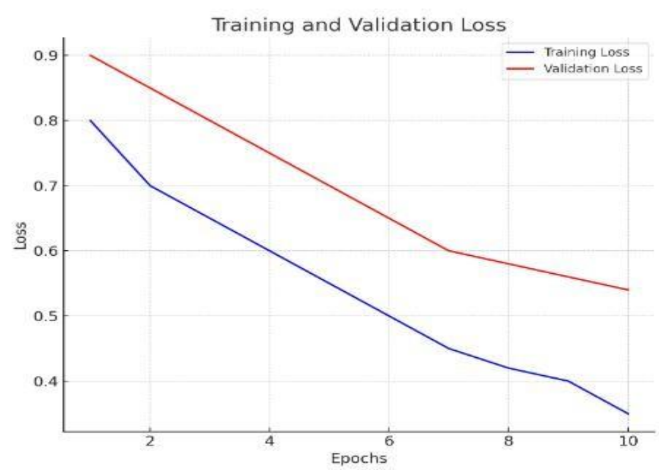

Fig 5 : Training and Validation Loss

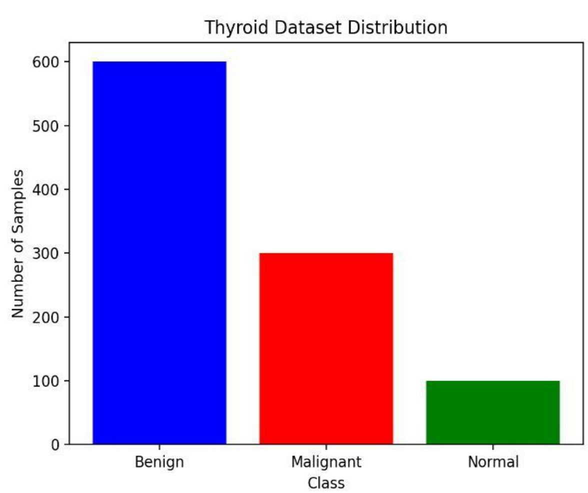

Fig 6 : Thyroid Dataset Distribution

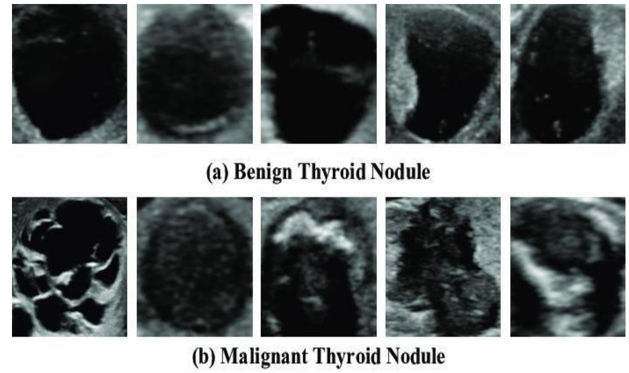

Fig 7 : Figure shows the shapes of Benign and Malignant thyroid nodules

V. Conclusion

In conclusion, this study Begins by preprocessing ultrasound images through resizing, intensity clipping, normalization, denoising, contrast enhancement (CLAHE), and sharpening to make features clearer. The images are then loaded into training and validation sets (80-20 split) with dimensions set to 256x256 for model compatibility.

A pre-trained ResNet50 model is adapted by adding layers for classification, allowing for efficient training on thyroid nodule detection via transfer learning. The model is trained for 10 epochs using the Adam optimizer with sparse categorical cross-entropy loss. Finally, it plots training and validation metrics, such as loss and accuracy, to assess the model's ability to accurately detect thyroid nodules. This approach supports accurate and efficient identification of thyroid nodules in medical imaging

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