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# IMPACT OF PREPROCESSING FILTERS ON THYROID DETECTION: LAPLACIAN FILTER AS AN OPTIMAL CHOICE

[1]Mahnoor Shahid, [2]Fahima Tahir, [3]Saima Farhan, [*4]Rabia Javed, [5]Khansa Aatif, [6]Wajeeha Malik

[1]Computer Science Department, Lahore College for Women University, Lahore, Pakistan
[2]Computer Science Department, Lahore College for Women University, Lahore, Pakistan
[3]Computer Science Department, Lahore College for Women University, Lahore, Pakistan
[*4]Computer Science Department, Lahore College for Women University, Lahore, Pakistan
[5]Computer Science Department, Lahore College for Women University, Lahore, Pakistan
[6]Computer Science Department, Lahore College for Women University, Lahore, Pakistan

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**Corresponding Author: * Rabia Javed**

## Abstract
*This study presents a comparative analysis of different image enhancement filters for automated detection and classification of thyroid nodules in ultrasound images. The primary objective was to evaluate how preprocessing techniques influence the diagnostic accuracy of deep learning-based models. Four filters Gaussian, Laplacian of Gaussian, Unsharp, and Laplacian were applied to a balanced dataset containing benign and malignant thyroid images. Each enhanced image set was used to train and test a classifier for nodule detection. The results demonstrated that the Laplacian filter achieved the highest classification accuracy of 99.27%, outperforming Gaussian (97.80%), Unsharp (92.44%), and Laplacian of Gaussian (90.98%) filters. The Laplacian filter's superior performance can be attributed to its second-order derivative operation, which accentuates rapid intensity transitions and enhances edge details critical for identifying the structural boundaries of thyroid nodules. These enhanced edge features allow the deep learning model to better distinguish between benign and malignant tissues. This study highlights that selecting an optimal image enhancement technique, particularly the Laplacian filter, significantly boosts diagnostic precision in computer-aided thyroid nodule detection systems.*

## 1. INTRODUCTION
Detection of a thyroid nodule is most important to save the patient's life. At the base of the neck, there is a small gland that produces hormones called the thyroid gland. The thyroid's function is to create thyroid hormones, which enter the circulation and reach every tissue in the body. The thyroid hormone helps the body stay warm, maintain energy, and keep the heart, muscles, brain, and other organs operating normally. It produces two major hormones, T3 and T4, in the bloodstream to control the body's metabolic rate and growth. A rare type of cancer that affects the thyroid gland is called a thy-roid tumor. A thyroid tumor is also called a nodule. In nodules, cells might develop abnormally, form-ing radiologically identifiable lumps. In the endocrine system, thyroid nodules are a common disease and usually appear as a solid, mixed, or cystic nodule

Thyroid nodule incidence has risen considerably in recent decades across the world. It is now the sixth most common malignancy in women and accounted for almost 3% of all cancer diagnoses (45,000 new cases) in the United States in 2010. The incidence increased from 3.6 per 100,000 in 1973 to 8.7 per

100,000 in 2002 [1]. Overall, 2.2% females in Pakistan are affected by Thyroid cancer and it has been shown to be more common in women than in men [2]. A thyroid nodule can be categorized as Benign Thyroid Nodule and Malignant Thyroid Nodule (Cancerous). A benign thyroid Nodule is a type of non-cancerous nodule that can grow but will not be spread. A malignant thyroid Nodule is a type of cancerous nodule that can grow and spread into nearby tissue. Detection of a thyroid nodule is most important to save the patient's life. Because physical examination and blood tests alone cannot typically tell whether a thyroid nodule is malignant, thyroid nodule evaluation frequently includes specialized procedures such as thyroid ultrasonography and fine needle biopsy. Imaging technology is used for the diagnosis of thyroid disease, which is usually done with Single-Photon Emission Computerized Tomography (SPECT), Ultrasound (US), computed tomography (CT), etc. There are many ways to detect thyroid nodules. An important technique for finding thyroid nodules is thyroid ultrasonography. The thyroid is photographed using high-frequency sound waves. This extremely precise test can quickly determine the exact size of a lump as well as whether a nodule is solid or fluid filled (cystic). Ultrasound can assist detect suspicious nodules since several thyroid nodule features are more prevalent in thyroid cancer than in noncancerous nodules. Thyroid ultrasound can detect nodules that would be difficult to detect during a physical examination [3].

Wenkai Yang et al. present a multitasking cascade deep learning model (MCDLM) to classify malignant and benign thyroid nodules using Ultrasound images to integrate radiologists' multidomain knowledge (DK). The dataset of Ultrasound images of 1030 patients was used. From which about 35% of data were Fully labelled. Experimental results on Ultrasound images can achieve an accuracy of 90.01% and an AUC of 91.07% [4].

ResNet, VGG19 and VGG16 models of the deep learning were implemented for the diagnosis of thyroid nodules. Results are also compared with diagnosis by four radiologists. A dataset of 15409 images was used. Furthermore, Datasets are grouped into validation (n = 3,082) and training (n = 12,327) sets. It was observed that VGG16 and ResNet50 show better results indicating AUC 0.86%, accuracy 0.78% and AUC 0.85% and accuracy 0.75% respectively on internal test sets [5].

To fill the gap that exists in using ultrasound images with convolutional neural networks to characterize thyroid nodules, Zhong Liu et al. proposed an information fusion-based joint convolutional neural network (IF-JCNN) method. In this research, multiple performance measures were evaluated and 91% accuracy for the proposed model was achieved [6].

Yuan Hang proposed a fusion of traditional as well as deep features. A total of about 428 samples, about 60% in the training set and about 40% in the test set were used in this study to achieve specificity (86.5%), sensitivity (95%), and accuracy (92.2%) [7].

Wan Zhu et al. proposed ANN-based ultrasound radionics before surgery in patients with healthy and papillary thyroid cancer. They used this model to predict massive lymph node metastasis. In this study, the combined model performed better, with an AUROC of 0.910% and an area under precision-recall of 0.463% [8].

Thyroid nodule detection was performed by extracting grey level co-occurrence matrix from Ultrasound images using machine learning algorithms i.e. SVM and ANN was performed and achieved accuracies 96% and 75% respectively. Image preprocessing was applied using median filter [9].

Among 983 transverse and longitudinal ultrasound images, 81 were used as test set while others were used in fivefold cross validation for the diagnosis of thyroid nodule. During cross validation five models for each view, ensembled with non-max suppression, were trained using extreme gradient boosting model. The proposed model results 63% specificity and a sensitivity of 84% [10].

A review of existing literature reveals that most studies on thyroid nodule detection have primarily focused on machine learning and deep learning approaches, with limited emphasis on the role of preprocessing and image enhancement techniques. Although ultrasound imaging is the most widely used modality for thyroid diagnosis due to its non-invasive, safe, and cost-effective nature, it often suffers from speckle noise, low contrast, and indistinct boundaries. Image enhancement techniques are therefore crucial for reducing noise, improving contrast, and emphasizing nodule edges, resulting in clearer visualization of thyroid structures. These enhancements significantly

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improve the accuracy of feature extraction and strengthen the reliability of computer-aided classification systems. The proposed research aims to investigate the impact of various preprocessing techniques on the detection and classification of thyroid nodules in ultrasound images.

## 2. MATERIALS AND METHODS

### 2.1 Dataset

The dataset was downloaded from the Kaggle website [11]. The dataset contains cancerous (malignant) and non-cancerous (benign) images of thyroid ultrasound, 683 each. Ultrasound images are mostly used in the identification and diagnosis of thyroid nodules. The most sensitive imaging technique for examining thyroid gland and related abnormalities is high-resolution ultrasound. In addition to being non-invasive, it is most accessible, affordable, and radiation-free, scanning. Basic classification of thyroid nodules is shown in Figure 1.

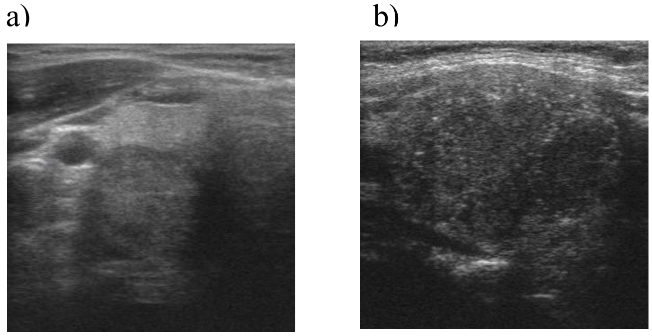


*Figure 1. Types of Thyroid Ultrasound Images a) Benign Thyroid b) Malignant Thyroid.*

Furthermore, the data for thyroid nodules classification is divided into train (70%), test (15%) and validation (15%) parts with their individual target labels. The dataset distribution is summarized in Table 1.



TABLE 1. DATASET DISTRIBUTION

| Benign Images | | | Malignant Images | | |
|---|---|---|---|---|---|
| Training Images | Testing Images | Validation | Training images | Testing Images | Validation |
| 335 | 205 | 143 | 335 | 205 | 143 |

### 2.2 Proposed Methodology

The proposed methodology is based on the use of CNN, a deep learning model for the classification of thyroid nodules which identifies and detects the nodule in thyroid gland using Ultrasound images. Different preprocessing techniques such as grey scaling, Laplacian, Gaussian, Unsharp, and Laplacian of Gaussian (Log) are also applied on the input images to monitor their effects on the classification. After application of preprocessing, a deep learning-based model will be trained using train data followed by model testing and performance evaluation. The basic flow of the proposed method for the classification of thyroid nodule is shown in Figure 2.

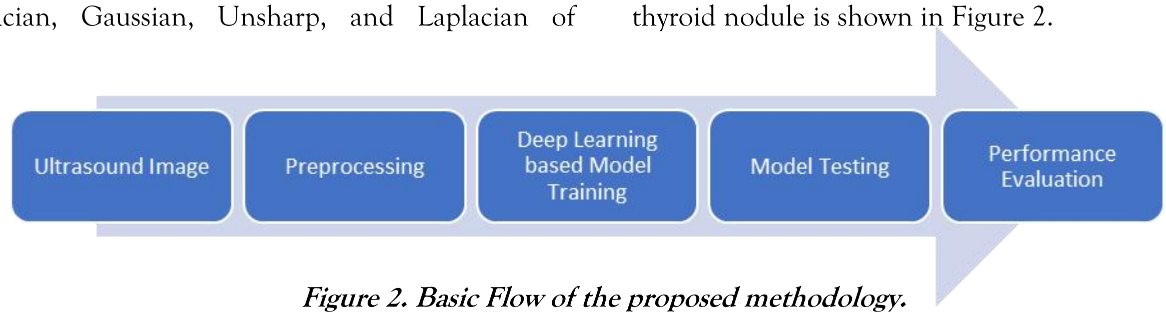


*Figure 2. Basic Flow of the proposed methodology.*

The detailed procedure of the proposed methodology for the classification of thyroid nodule is shown in Figure 3.

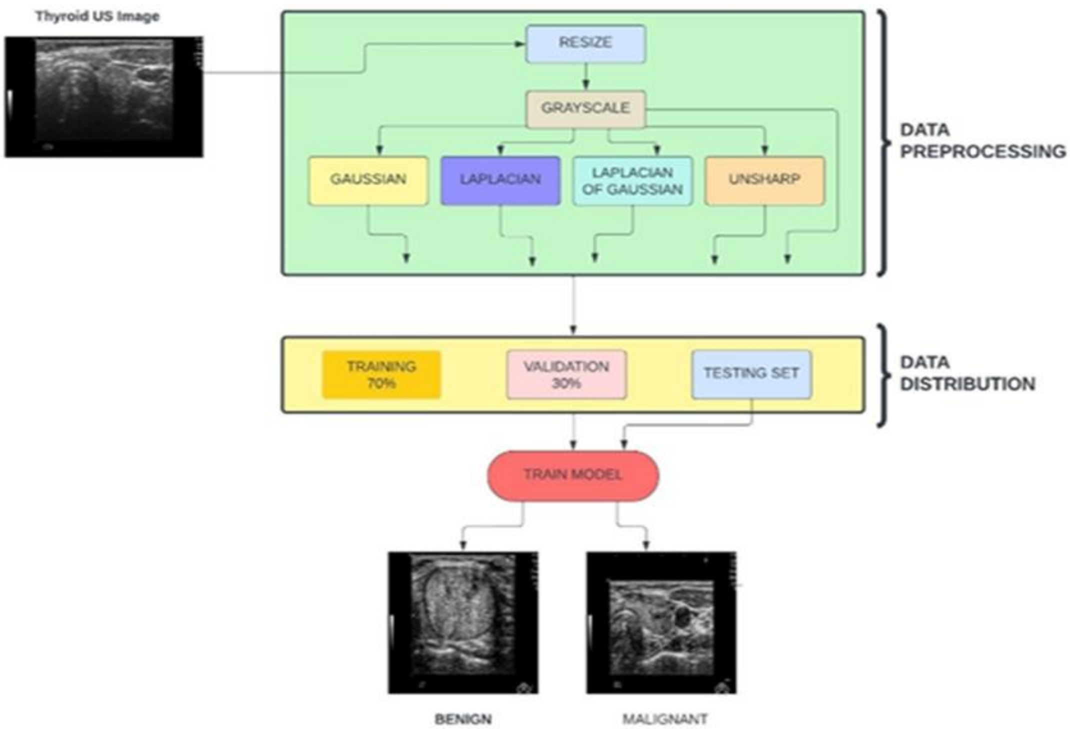


*FIGURE 3. DETAILED DIAGRAM FOR THYROID NODULE CLASSIFICATION*

**2.3. Data Pre Processing**

Preprocessing data is a very important task when dataset images have different intensity ranges. A series of preprocessing operations is essential to ensure stable and efficient training of the experimental network. The preprocessing operations help in accuracy and classification results improvement. The dataset of thyroid ultrasound images is available in a .mat file. Each thyroid image size is different. Firstly, the resizing of thyroid image dimension is 227x227 pixels. The preprocessing steps for the dataset of thyroid ultrasound images are shown in Figure 4.

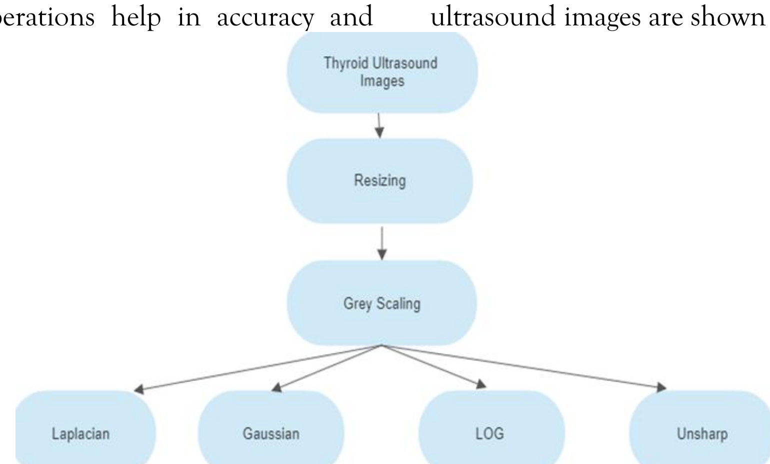


*FIGURE 4. PREPROCESSING STEPS FOR THYROID DATASET*

### 2.3.1 Image Resizing
The first pre-processing step is image resizing. Resizing an image changes its dimensions, which often has an impact on the image's file size and quality. The size of the resized thyroid nodule picture is 227x227 pixels.as known in Figure 5a.

### 2.3.2 Grey-Scaling
The resized image is then converted to the grayscale format as shown in Figure 5b.

### 2.3.3 Laplacian
In Image processing, a second-order derivate filter which is used for edge detection called Laplacian is applied on the grayscale image [12]. The results of the filter are as shown in Figure 5c.

### 2.3.4 Gaussian
In Image Processing, the Gaussian filter is used to remove noise from the image [13]. The thyroid nodule after applying Gaussian filter is shown in Figure 5d.

### 2.3.5 LOG (Laplacian of Gaussian)
A well-liked edge detection approach is the Laplacian of Gaussian. Applications for image processing and computer vision rely heavily on edge detection [13]. It is used to identify borders, find objects, and extract characteristics. The nodule after applying LOG is shown in Figure 5e.

### 2.3.6 Unsharp
The unsharp masking technique originates from a traditional method used in the publishing industry to enhance image sharpness by subtracting its blurred (unsharp) version[14]. Despite its name, this filter functions purely as an image sharpening operator, as illustrated in Figure 5f.

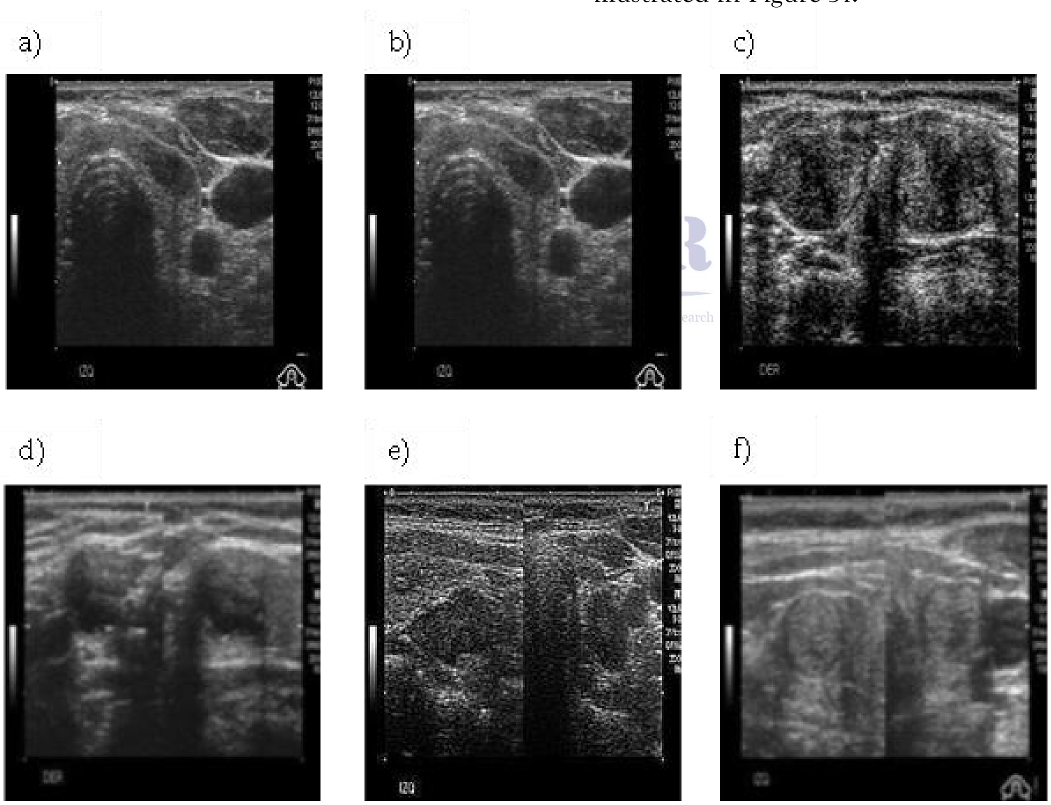


***FIGURE 5. Effects of different pre-processing techniques on Thyroid nodule image a) Resized Image b) Grayscaled c) Laplacian Filter d) Gaussian e) LOG f) Unsharp.***

### 2.4 Thyroid Nodule Classification
CNN 15-layer architecture was used for classification. The value of Input layer is (227, 227, 1) in which the dimension of image is 227x227 with 1 channel. The size of filter is 3x3 and 16 channels with the same padding used in first layers. A max-pool layer is used which stride value (2, 2). The next Convolutional layers have 3x3 filter size with 32 channels and the max-pool layer has also stride value is (2, 2) as defined in the previous maxpool layer. Batch Normalization is

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a method intended to regulate the inputs in a deep learning neural network into a layer automatically. Here 1 Batch Normalization layers are added after each convolutional layer. In the next layers of architecture, there are three con-volutional (Conv) layers and a max-pool layer having the value of filter size is 3x3 and 64 channels with the same size of padding. In the next phase, three new layers add such as: one is fully connected layer and other two layers are dense layers. The activation functions such as: Rectified Linear Unit (ReLU) and Softmax are used in this architecture. The number of epochs for the proposed model is 30 along with a batch size of 128. This proposed method generates the best results having all parameters set value. The proposed CNN (15 layers) architecture is shown in Figure 6. The performance measures such as accuracy, sensitivity, specificity, recall and precision are used to evaluate the performance of the proposed method.

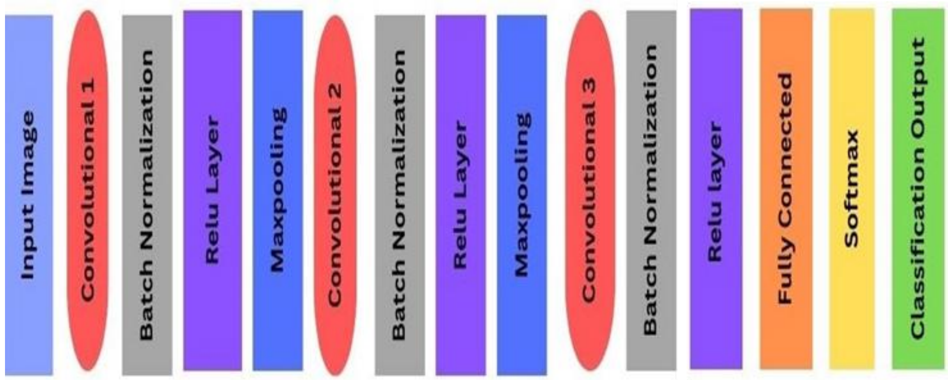


*FIGURE 6. PROPOSED 15-LAYER CNN ARCHITECTURE*

## 3. RESULTS AND DISCUSSION

Four different experiments were performed to evaluate the effects of preprocessing techniques on classification of thyroid nodules. Image resizing and gray scaling were considered as base steps for the application of image enhancement filters for preprocessing.

1) Experiment 1: (Base Steps followed by Gaussian)
2) Experiment 2: (Base Steps followed by Laplacian of Gaussian)
3) Experiment 3: (Base Steps followed by Unsharp)
4) Experiment 4: (Base Steps followed by Laplacian)

### 3.1 Experiment 1: (Base Steps followed by Gaussian Filter)

The experiment 1 was based on the application of Gaussian filter after base steps as preprocessing for the classification of thyroid nodule and a test accuracy of 97.80% was achieved. The number of epochs for experiment 2 set to 30. The confusion matrix for the results is shown in Figure 7.

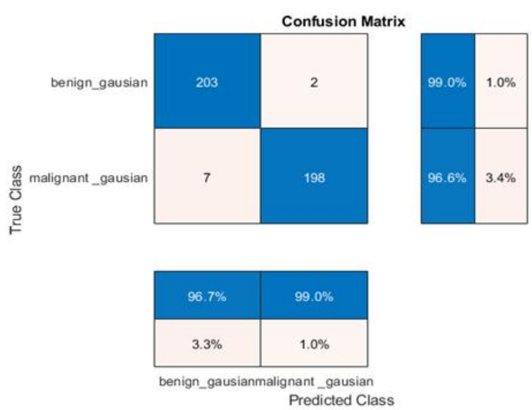


*FIGURE 7. CONFUSION MATRIX FOR EXPERIMENT 1.*

**3.2 Experiment 2: (Base Steps followed by Laplacian of Gaussian)**

Laplacian of Gaussian was used as preprocessing filter for image enhancement in Experiment 2 and results in a test accuracy of 90.98% achieved. The number of epochs for experiment 3 was set to 30. The confusion matrix was shown in Figure 8.

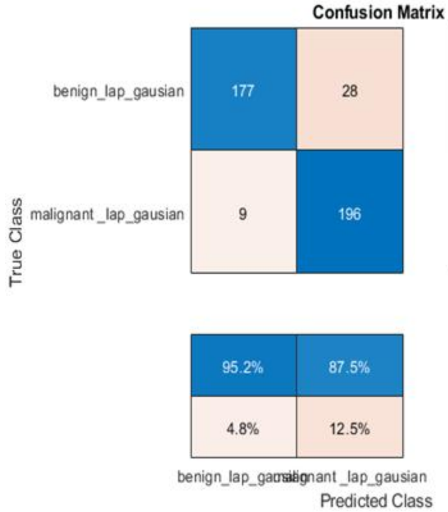


*FIGURE 8. CONFUSION MATRIX FOR EXPERIMENT 2*

**3.3 Experiment 3: (Base Steps followed by Unsharp)**

Classification was performed using unsharp filter as image enhancement technique in Experiment 3 for the detection of thyroid nodule and test accuracy improved to 92.44%. Figure 9 clarifies the results using confusion matrix of experiment 3.

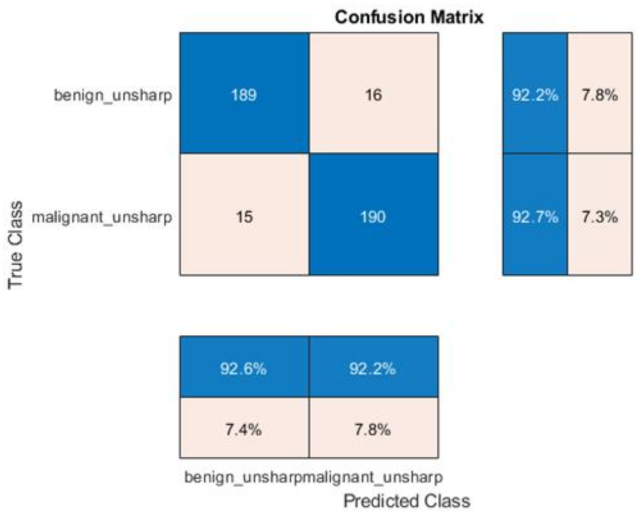


*FIGURE 9. CONFUSION MATRIX FOR EXPERIMENT 3*

**3.4 Experiment 4: (Base Steps followed by Laplacian)**

A test accuracy of 99.27% for the classification of thyroid nodule was achieved as shown by the confusion matrix in Figure 10, when Experiment 4 was applied to evaluate the effects of Laplacian fil-ter on the images used for classification purposes.

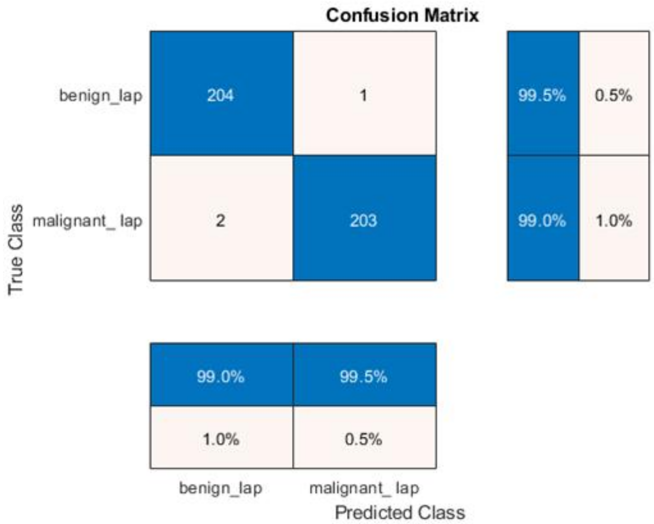


*FIGURE 10. CONFUSION MATRIX FOR EXPERIMENT 4*

The detailed results of all four experiments are shown in Table 2. The experimental outcomes clearly demonstrate that the choice of image enhancement technique has a decisive influence on the performance of automated thyroid nodule classification. Among the tested methods—Gaussian, Laplacian of Gaussian, Unsharp, and Laplacian—the Laplacian filter achieved the highest accuracy of 99.27%, proving to be the most effective for enhancing ultrasound imagery. This superior performance can be attributed to the Laplacian filter's capacity to emphasize local intensity variations and highlight edge boundaries, which are critical for differentiating the irregular textures and shapes characteristic of malignant nodules. By amplifying high-frequency components, it enables the learning model to ex-tract more discriminative spatial features, thus reducing misclassification. In contrast, smoothing filters such as Gaussian tend to blur fine structural details, potentially diminishing the diagnostic cues necessary for precise boundary detection. The Laplacian's focus on second-order derivatives enhances contrast in homogeneous regions and sharpens edges, making it particularly suitable for medical im-aging applications where lesion boundaries are subtle. These findings confirm that applying the Laplacian filter during preprocessing optimizes feature clarity, supports robust model convergence, and ultimately improves the reliability of computer-aided diagnosis for thyroid nodule detection.

TABLE 2. DETAILED RESULTS OF ALL FOUR EXPERIMENTS

| Experiments | Training acc. | Testing acc. | F1-score | Recall | Precision |
|---|---|---|---|---|---|
| 1 | 0.9371 | 0.9780 | 0.9782 | 0.9783 | 0.9780 |
| 2 | 0.9479 | 0.9098 | 0.9115 | 0.9133 | 0.9098 |
| 3 | 0.9619 | 0.9244 | 0.9244 | 0.9244 | 0.9244 |

## 4. CONCLUSIONS

The experimental evaluation confirmed that preprocessing filters have a substantial impact on the accuracy of thyroid nodule classification. Among the tested filters, the Laplacian filter delivered the best performance due to its strong edge-detection capability and ability to emphasize fine textural differences between benign and malignant nodules. Unlike smoothing-based filters such as Gaussian, the Laplacian method amplifies pixel intensity variations, improving the model's sensitivity to micro-structural changes in ultrasound imagery. Consequently, the Laplacian filter enhances the discriminatory power of deep learning algorithms, making it an effective preprocessing approach for improving the robustness and diagnostic reliability of thyroid nodule detection systems.

**Data Availability Statement:** For experimentation of the proposed research a publicly available dataset was used and link is already mentioned in material and methods.
**Conflicts of Interest:** Authors declare no conflict of interest

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