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# Comparison of Various Segmentation Techniques for Thyroid Disorder Detection

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**Abstract**
Millions of people worldwide suffer from thyroid diseases, which weaken energy, metabolism, and general health and call for prompt and precise diagnosis. One essential non- invasive diagnostic technique for identifying anomalies is thyroid ultrasonography imaging. This study looks at common thyroid conditions, the use of ultrasonography as a diagnostic tool, and several image segmentation methods for thyroid ultrasound image analysis. A thorough comparison of both conventional and sophisticated segmentation techniques is being done, assessing each one's performance using measures like Accuracy and F1 Score. With a remarkable accuracy of 98.58% and an F1 Score of 98.49%, the AWMF+RBF Neural Network proved better than other alternative techniques for segmentation tests. The accuracy of other competitive approaches, such as Modified Normalized Cut (N- cut) and Extreme Learning Machine (ELM), was 95.28%.
With complex image data, traditional methods such as ACWE, SVM, and Local Active Contour performed somewhat well, exposing their shortcomings. Hybrid approaches that combined anisotropic weighted median filter (AWMF) with other models improved the results. This study studies segmentation algorithm and shows effectiveness of neural based approaches.

**Keywords**: Automated analysis, Diagnostic tools, Thyroid disorder, segmentation techniques, Ultrasound imaging.

## 1. Introduction

In medical allied fields, healthcare industries, image segmentation helps in early identification and detection of many complex disorders. Thyroid disorders that are very common endocrine disorder worldwide, is one such example . Women are particularly susceptible to thyroid-related problems, which affect nearly 42 million individuals in India alone. As thyroid functioning directly affects most of our organs, precise and accurate recognition of thyroid diseases are of great importance.
The thyroid gland, a tiny butterfly shape gland located in the neck produces two active hormones, levothyroxine (T4) and triiodothyroine (T3) which are important in the production of proteins, regulation of the body temperature, and in overall energy production and regulation.
Four types of thyroid diseases are of main interest: Hypothyroidism, Hyperthyroidism. Hashimoto's thyroiditis (autoimmune thyroiditis), and thyroid cancer.
A popular non-invasive technique for assessing thyroid health is ultrasound imaging because of its excellent sensitivity and affordability. It can be difficult to understand these visuals, though. Speckle

noise, poor contrast, and tissue resemblance are common issues with ultrasound images that make manual diagnosis challenging and time-consuming.

Image segmentation is used for partitioning a complex image into multiple meaningful segments that can be further examined. It can help separate important areas such as tumors, lesions, or nodules, improving diagnostic accuracy. In this paper, the focus is on use of image segmentation in improving thyroid ultrasonography analysis**.** Various segmentation methods, ranging from conventional methods to sophisticated methods like machine learning based algorithms, including hybrid models, AWMF, RBF NNs, or neural networks etc are being assessed.

In this paper, a comparison between their performances, based on accuracy and F1 Score criteria, is made, to find which approach is best suited for the said medical diagnosis using ultrasound images. This supports the ultimate objective of creating an efficient, automated method for thyroid disorder detection. For automated and accurate interpretation, a variety of segmentation approaches have evolved over the time.

Early traditional Segmentation Approaches used conventional techniques like threshold technique, edge detecting algorithms, region-based techniques, Active Contour models, graph based Normalised cut(N cut) models etc. These methods work well with structure but have their limitations when faced with noise, poor contrast ,poor visuals etc.In recent years, using techniques like AWMF, machine learning, neural networks etc have greatly improved the performance.

## 2. Related Work: Imaging and Segmentation of Thyroid disorders:

Computer-aided studies of thyroid disorders and diagnostic systems using Ultrasound imaging, rely heavily on thyroid image segmentation as Thyroid glands and nodules must be well defined from ultrasound images for proper evaluation.

There have been dozens of studies on thyroid gland segmentation and thyroid nodule segmentation in ultrasound images [1]. By dividing the image into distinct segments successfully, the segmentation process isolates suspicious nodules or areas of interest, from nearby structures[2]. For proper segmentation, advanced algorithms are necessary as intrinsic features such speckle noise, poor contrast, and blurring borders make it difficult to interpret thyroid ultrasound images [3]. Additionally, segmentation procedure becomes much more difficult due to the significant variation in nodule size and appearance.

### 2.1 Shape-Based and Contour-Based Techniques.

In conventional segmentation techniques, one of the important subset are contour and shape-based techniques. In these methods, gradient data and shape properties are examined. These methods mainly concentrate on defining borders. For thyroid nodule segmentation, the Active Contour Without Edges (ACWE) model, put out by Chan and Vese, has been mostly used [4]. This method evolves a contour using regional statistics as against gradient information and hence is comparatively resistant to image noise. The Distance Regularized Level Set (DRLSE) uses a distance regularization term to preserve the level set function's steady development. Although it frequent parameter adjustments to get good results, this method has been effective for thyroid ultrasound segmentation [5]. These techniques are usually involve initializing a contour, which makes them semi-automatic and may introduce variations depending on the initial configuration .

### 2.2 Approaches Based on Regions.

Region-based segmentation techniques organize pixels into areas based on shared attributes. In comparis on research, the Localized Region Based Active Contour (LRAC) method has proved to be better than both ACWE and DRLSE methods. This approach is more flexible to the variable nature of thyroid ultrasound images as it takes into account local image statistics. In thyroid imaging, another conventional region-based techniques, the Variable Background Active Contour (VBAC) approach, deals with the problem of uneven background distribution. It works well for nodules that are hypoechoic, although, it has trouble with non-hypoechoic nodules that show less contrast with the surrounding tissue. The Joint Echogenicity-Texture (JET) model is a modification to VBAC. It combines both regional pixel intensity and texture feature distribution, thus enhancing segmentation performance, especially for isoechoic thyroid nodules. Researchers have also looked at merging complimentary methods, including integrating ACWE with the energy model known as Region-Scalable Fitting (RSF). Although this hybrid technique produces excellent results, its practical efficiency is limited by the need to preset an initial shape and lengthy iterations[6].

**2.3 Convolutional Neural Networks and U-Net Variants.**

Introduction of deep learning, has completely changed medical image segmentation. Convolutional Neural Networks (CNNs) have shown impressive performance in thyroid ultrasound image analysis . the U-Net architecture—that is distinguished by its encoder-decoder structure with skip connections—has become the industry standard for Medical image segmentation tasks, such as thyroid nodule delineation [7]. The traditional U-Net has drawbacks because of its fixed receptive field, that makes it difficult to separate objects of different sizes—a problem that is frequently encountered with thyroid nodules. Since then, there have been modifications made to U-Net. Multi-scale U-Net (MSUNet) combines outputs from convolution kernels with various receptive fields by introducing multi-scale blocks in each encoder layer, in order to obtain more varied features and intricate spatial information.

Three important improvements to the regular U-Net are incorporated into the deformable- pyramid split-attention residual U-Net (DSRU-Net), which is a note worthy advancement:

1. ResNeSt blocks for better feature extraction, which are especially useful for segmenting tiny targets
2. Atrous Spatial Pyramid Pooling (ASPP), used to record multiscale contextual data of different sizes and shapes.
3. Deformable convolution v3, that can adapt to various spatial structures and geometric variations are used to enhance image segmentation tasks, specially where objects have complex shapes or are hidden by other objects.

With an average dice coefficient of 92.5% and a nodule dice coefficient of 94.1%, experimental assessment show that DSRU-Net was superior to both conventional methods and standard U-Net implementations.

**2.4 Transformer-BasedArchitectures**

Recent developments in computer vision have introduced Transformer designs, first created for natural language processing, have been included into medical image segmentation frameworks. For thyroid nodule segmentation, a new method that uses a Swin U-Net architecture have demonstrated encouraging results.

In this model, the capabilities of the Swin Transformer to collect contextual information and long-range relationships are combined with the advantages of the U-Net architecture. In order to enhance edge preservation and feature extraction, the design incorporates multiscale convolutional structures and residuals into the encoder route. Long skip connections are fed into an attention module. Edge blurring and nodule size fluctuation, two prominent issues in thyroid ultrasound imaging are successfully addressed by this method. Comparative analysis show that the Swin U-Net design outperforms baseline models such as the conventional U-Net and DeepLabv, with an average Dice Similarity Coefficient (DSC) of 0.78. Even under difficult imaging conditions, the attention mechanism allows the model to reduce noise and concentrate on pertinent characteristics, producing more accurate segmentation borders.

### 2.4. Comparative Analysis of Segmentation Methods

#### 2.4.1 Performance Metrics and Evaluation:

It is necessary to use strong measures that represent clinical usefulness when assessing segmentation performance. Various classification metrics (accuracy, precision, recall) and segmentation metrics (Dice, IoU) are examples of common assessment measures[8]. These metrics compare algorithm outputs with ground truth annotations, usually supplied by seasoned radiologists, to offer a quantitative evaluation of segmentation quality. Because various measures highlight different facets of segmentation performance, choosing the right assessment metrics is essential. For example, the Dice coefficient precisely evaluates the spatial overlap between the predicted and ground truth segmentations, making it especially useful for medical applications, even if accuracy offers an overall measure of accurate classifications [9]. Comparative research shows that different segmentation techniques function differently.

Even though they make sense conceptually, traditional active contour models like ACWE often perform mediocre, with accuracy rates between 85 and 90%. On the other hand, sophisticated deep learning techniques like DSRU-Net exhibit far more accuracy, with dice coefficients over 92% [10]. This disparity in performance highlights how deep learning has revolutionized medical image segmentation.

#### 2.4.2 Strengths and Limitations of Various Approaches

Every segmentation strategy has unique benefits and drawbacks. When compared to deep learning techniques, conventional contour and region-based algorithms often require less training data and processing resources. Additionally, they make their decision-making process more transparent, which can be helpful in clinical contexts where interpretability is crucial. Nevertheless, complex picture features including poor contrast, speckle noise, and blurry borders that are frequently seen in thyroid ultrasound images are difficult for these techniques to handle[6]. CNN-based architectures like U-Net and its derivatives exhibit extraordinary robustness against imaging artifacts and anatomical variations34, demonstrating the greater adaptability of machine learning and deep learning techniques to difficult imaging settings. However, these approaches usually need a large amount of annotated training data and a significant amount of processing power, which may restrict their use in contexts with limited resources [11].

The state-of-the-art is represented by transformer-based architectures such Swin U-Net, which successfully use self-attention processes to balance local feature extraction with global contextual awareness. Despite their remarkable segmentation accuracy, these methods' memory needs and computational complexity make them difficult to apply, especially for real-time applications.

#### 2.4.3 Recent Innovations and Future Directions

##### 2.4.3.1 Hybrid and Multitask Approaches

Hybrid techniques that incorporate the complementing capabilities of several segmentation methodologies have come into the focus of recent study. The combination of deep learning frameworks with conventional image processing approaches has demonstrated encouraging outcomes.

Another interesting approach is multitask learning, which tackles detection and segmentation problems at the same time. Multitask techniques are better in line with clinical practice for thyroid nodule evaluation by simultaneously segmenting suspicious areas and identifying images that may contain nodules [12]. Through shared feature learning across related activities, this integrated strategy improves clinical translatability and may lead to an improvement in overall performance.

**2.4.3.2 Addressing Dataset Limitations**

A recurring obstacle in the advancement of thyroid ultrasound segmentation research is the scarcity of extensive, varied, and well annotated datasets. Establishing standardized thyroid ultrasound image libraries with expert annotations would help future research by enabling more relevant comparisons between algorithms and speeding up methodological advancements. [13]

Utilizing semi-supervised and unsupervised learning approaches to lessen reliance on manually labeled data is another exciting avenue. These methods might possibly overcome a significant barrier in deep learning applications and uncover the benefits of bigger unlabelled datasets.

## 3. Proposed System/ Methodology

In order to enhance the segmentation of thyroid ultrasound images and aid in the detection of thyroid problems, this study offers a multi-step technique. We examine and contrast a number of conventional and cutting-edge segmentation algorithms in light of the complexity of ultrasound imaging, which is frequently impacted by noise, low contrast, and minute structural variations. Each method has a unique role in image processing, helping in isolation of thyroid gland abnormalities or nodules.

### 3.1 Anisotropic weighted Median Filter (AWMF) preprocessing

Many ultrasound images are preprocessed using AWMF prior to segmentation. It smoothens the image while maintaining crucial edge information, in contrast to conventional median filters that could blur delicate edges. This is done by adjusting the filtering power according to the intensity and direction of neighboring pixels. It preserve the structural integrity of thyroid tissue borders while lowering the speckle noise.

The filter computes a weighted median of pixels in a local neighborhood:

$$I'(x,y) = \text{median}\ \{ w_{i,j}\ .\ I\ (x + i\ ,y,\ \ y + j)\} \qquad (3.1.1)$$

where:

- I(x,y) is the original image intensity,
- $w_{i\ j}$ is the anisotropic weight based on gradient direction and distance,
- $I'$(x, y) is the filtered output at position(x,y)

### 3.2 Radial Basis Function Neural Network (RBF NN)

RBF Neural Networks is particularly good at approximating functions and recognizing patterns. This method filters the image using AWMF before using the RBF NN. The network maps the input pixel data to outputs (segmented areas) using radial basis functions as activation functions in its hidden layer. RBF is used since it can quickly adjust to nonlinear patterns in the image.It is useful for recognizing intricate thyroid structures.

$$f(x) = \sum_{i=1}^{N} w_i\,.\,\emptyset(\|x - c_i\|) \qquad (3.2.1)$$

Where:

- x is the input feature vector (e.g., intensity, coordinates),
- $w_i$ are output layer weights,
- $c_i$ are the centres of radial basis functions,

- $\varnothing(\mathrm{r}) = e^{-\gamma r^2}$ is the Gaussian RBF function
- $\|x - c_i\|$ is the Euclidean distance between the input vector 'x' and the center 'ci' of the i-th RBF.

### 3.3 Extreme Learning Machine (ELM)

It is a feedforward neural network with a single hidden layer where the weights of ELM are assigned at random rather than incrementally. It uses a least-squares solution to calculate the output weights all at once that allows it to memorize intricate patterns at a very high speed. For thyroid image segmentation, it functions as a lightweight substitute for computationally demanding deep learning models, by learning from pixel intensity and spatial patterns. It gives good results in identifying important image areas.

$$H.\beta = T \Rightarrow H^{\dagger} T \qquad (3.3.1)$$

where

- H is the hidden layer output matrix,
- β are the output weights,
- T is the target label matrix,
- $H^{\dagger}$ is the Moore–Penrose pseudo-inverse of H

### 3.4. Modified Normalized Cut (N-cut)

It is a graph-based segmentation technique. It treats the image as graph, with pixels acting as nodes connected by edges that represent the relation ( both total similarity within the group and also the total dissimilarity between the groups). In order to maximize the similarity inside each segment and decrease the dissimilarity across segments, the "cut" divides the graph. The updated version includes changes to better handle inhomogeneous textures and weak borders, among other things, for better performance on medical photos. This method works very well for segmenting thyroid tissues with hazy or uneven boundaries

$$N_{cut}(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} \qquad (3.4.1)$$

Where

$\mathrm{cut(A,B)} = \sum_{u \varepsilon A, v \varepsilon B} w(u,v)$

$\mathrm{assoc(A,V)} = \sum_{u \varepsilon A, t\, \varepsilon\, B} w(u,t)$

### 3.5 Active Contour Without Edges (ACWE)

Rather of depending solely on edges, ACWE is a kind of level-set technique that uses region- based information to develop a curve for picture segmentation. In ultrasound imaging, where edge information is frequently erroneous, this is helpful. An energy function that takes into account the variation in pixel intensity inside and outside the contour is minimized by ACWE. This enables it to progressively adapt, even at low contrast, to the shape of the thyroid gland or any internal nodule.

$$E(C) = \mu \cdot \text{Length}(C) + \lambda_1 \int_{\text{inside}(C)} |I(x,y) - c_1|^2 dxdy + \lambda_2 \int_{\text{outside}(C)} |I(x,y) - c_2|^2 dxdy$$

Where

- $c_1, c_2$ are the average intensities inside and outside the contour,
- $\lambda_1, \lambda_2$ lambda are weighting parameters

### 3.6 SVM or Support Vector machine

Supervised learning model, SVM classifies the data by finding the best hyperplane to divide data into distinct groups. SVM can categorize individual pixels for image segmentation by considering contextual factors and pixel intensity. It works especially well when paired with feature extraction methods. It serves as a conventional benchmark in this system to assess the relative performance of machine learning alone versus more sophisticated or mixed approaches.

**3.7 Local Active Contour Model**

This variant of the active contour model concentrates on local visual characteristics instead of emphasizing global intensity. It is extremely beneficial when dealing with intensity inhomogeneities, that are frequent in medical images. Local region statistics drive the curve evolution, enabling the model to adjust to subtle and localized changes in the image, like tiny nodules in thyroid tissues or micro-calcifications.

**3.8 The AWMF watershed Preparation**

A region-based segmentation technique called Watershed handles the image as though it were a topographic surface. Basins are filled with simulated water at varying intensities to "flood" the area. Segmentation borders are formed as waters from many sources converge. Despite its strength, the technique is susceptible to noise, which is why our methodology combines it with AWMF to decrease incorrect segmentation brought on by speckle patterns.

**3.9 ACM or Active Contour Model**

ACM, sometimes referred to as "snakes," grows a curve by taking into account both external energy from picture elements like gradients and internal energy (such as curve smoothness). The curve helps segment areas with distinct edges because it is drawn to object boundaries. In order to enhance its capacity to identify subtler or more diffuse characteristics in thyroid pictures, ACM and AWMF are coupled in this work.

The suggested method for identifying thyroid disorders in ultrasound pictures uses a multi- phase, organized pipeline that is intended to improve diagnostic precision and dependability.

The method starts by inputting preprocessed thyroid images. It incorporates image improvement and restoration procedures to reduce speckled noise. Sharpening and smoothing operations are done to eliminate small artifacts while maintaining significant structural boundaries. Contrast enhancement techniques are then used to create a sharper and more detailed image for examination

After preprocessing, image segmentation is used on the enhanced image. It is used to separate important areas like cysts, nodules, or the thyroid gland itself. This step makes use of a number of segmentation techniques, such as active contour models to outline complicated structures, thresholding for basic intensity-based separation, edge detection algorithms for boundary tracing, and region-based techniques for grouping comparable pixels. Also, morphological methods are used to eliminate noise and rectify defects in shape in order to improve the segmentation results.

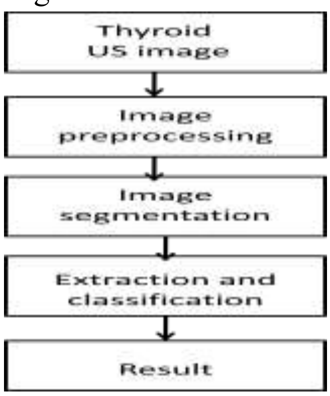


**Figure no.1: Flowchart Of Steps Used In Thyroid Disorder Detection Of US Images**

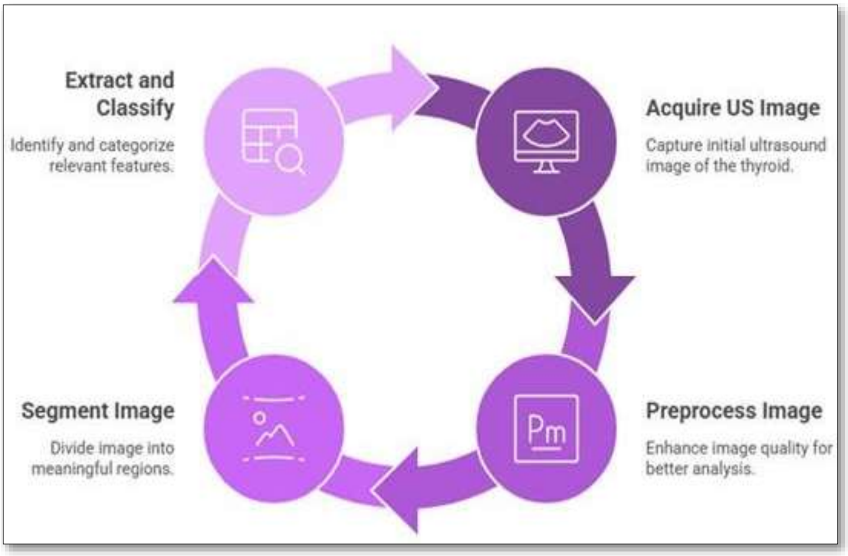


**Figure no.2: Cycle Of Thyroid Disorder Detection**

After segmentation, next step is feature extraction and classification. Machine learning techniques are used to assess the segmented regions and extract relevant properties that include shape, texture, and intensity. These classifiers are trained on labeled data and can determine whether segmented region is normal or suggestive of a thyroid condition. The system's final output is a diagnostic result, that offers impartial evaluation for thyroid disorder detection.

**Results and Discussion:**

**Table1. Comparison Between Various Segmentation Techniques**

| Technique | Accuracy | F1 Score |
|---|---|---|
| AWMF+RBFNN | 0.9858 | 0.9849 |
| ELM | 0.9528 | 0.9524 |
| Modified N-cut | 0.9528 | 0.9517 |
| ACWE-VBAC | 0.934 | 0.9326 |
| N-cut | 0.9292 | 0.9277 |
| AWMF+ACM | 0.9245 | 0.9228 |
| SVM | 0.9151 | 0.9134 |
| AWMF+Watershed | 0.8868 | 0.8833 |
| ACWE | 0.8396 | 0.8381 |
| Local Active Contour | 0.816 | 0.8154 |

Best accuracy and F1 score was given by AWMF+RBFNN neural network. The nonlinear classification strength of the RBF neural network and noise-suppressing and edge-preserving capabilities of AWMF are responsible for this method's success. Next,with same accuracy scores, Modified N-cut and ELM (Extreme Learning Machine) both gave good results. Quick training and strong generalization on structured data helped in ELM’s performance. With the help of improved graph-based segmentation, modified N-cut efficiently separates the complex areas in ultrasound images.

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The Bayesian architecture of the ACWE-VBAC approach, that controls uncertainty in contour evolution, contributed to its strong performance as well. Because of its versatility, it is especially appropriate for tissue-based structural segmentation.

Next were AWMF + ACM and traditional N-cut methods that provided average results. Although N-cut's segmentation is computationally efficient, it is less sensitive to intensity changes. The preprocessing advantage of AWMF + ACM is limited by the active contour models' sensitivity to the beginning conditions. Although it depends on precise segmentation, SVM offers a robust classification foundation. Its performance may plateau in the absence of adaptive segmentation or improved preprocessing. Because of the watershed algorithm's tendency to over-segment, particularly in noisy data, the AWMF + Watershed approach performed comparatively poor.

Lastly, the least successful methods were ACWE and Local Active Contour, which demonstrated their inability to handle noisy and poor contrast ultrasound pictures without improvement or learning-based guidance.

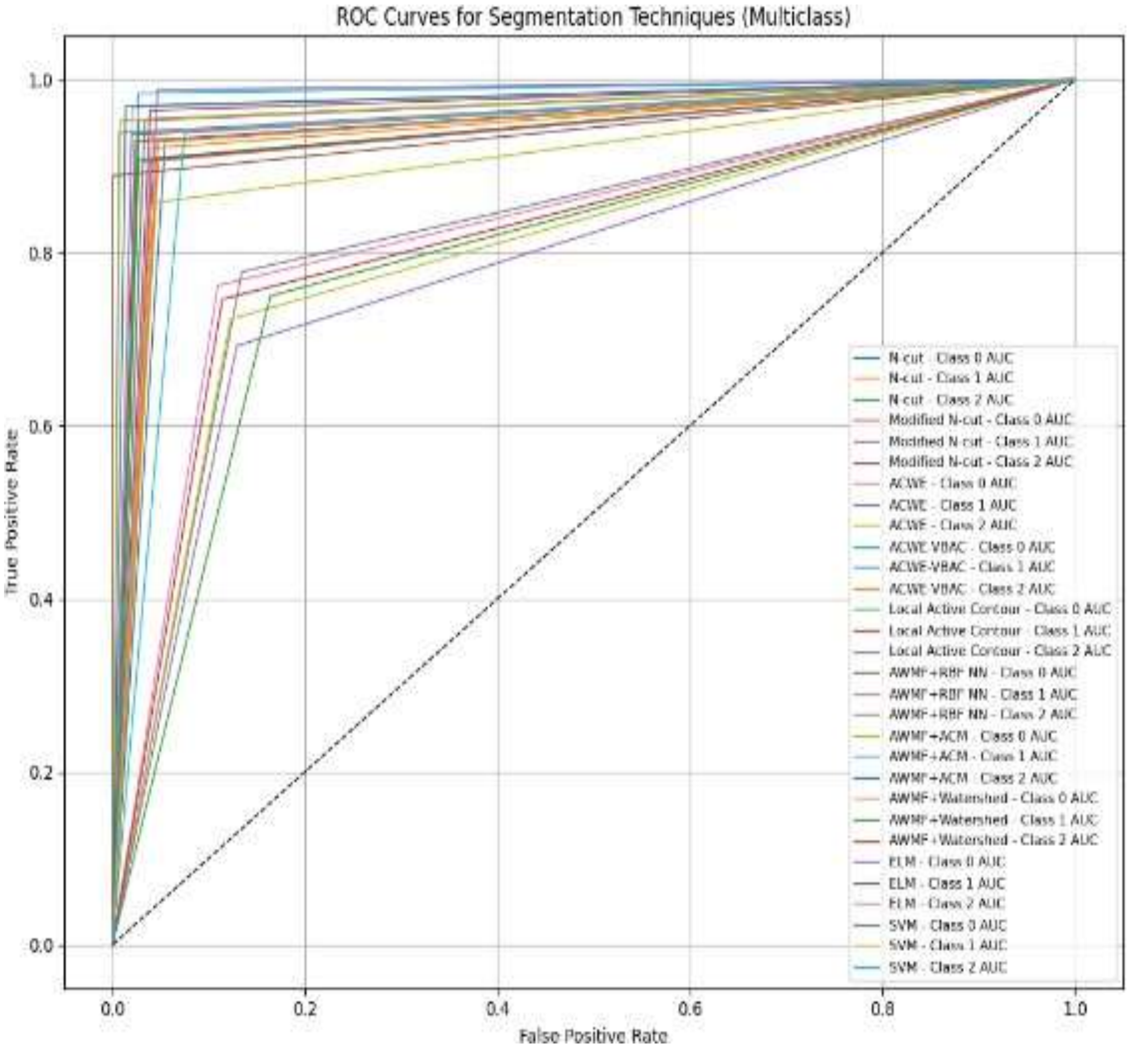


**Fig 3. ROC curves for various segmentation techniques**

The ROC curves for various segmentation strategies applied to a multiclass classification issue with three classes (Class 0, Class 1, and Class 2) are shown in this diagram. One-vs-rest analysis is used to assess each technique, producing distinct ROC curves and AUC values for every class. In addition to machine learning classifiers like SVM and ELM, the segmentation techniques include more

sophisticated hybrid models like AWMF paired with RBF Neural Networks, ACM, and Watershed, as well as more conventional approaches like N-cut and Active Contours (ACWE, Local Active Contour).
Better performance is shown by methods with ROC curves nearer the top-left corner, which achieve greater true positive rates and lower false positive rates. In all three classes, methods like AWMF+ACM, AWMF+RBFNN, and ELM show excellent classification performance.
In multiclass image segmentation, hybrid filtering and learning-based approaches perform better than traditional segmentation techniques, according to this statistical analysis.

**Conclusion**

Accurate and effective diagnostic methods are necessary for thyroid problems, which impact millions of people worldwide. Segmentation-driven ultrasound-based CAD systems improve diagnosis accuracy and lessen clinical workload. This study examined various segmentation techniques, highlighting deep learning innovations (e.g., MG-UNet, TRFE+) and included a performance comparison of conventional approaches (e.g., AWMF+RBF NN, ACWE- VBAC). With an accuracy of 0.9858, the AWMF+RBF neural network outperforms conventional techniques, and deep learning models attain higher Dice scores (up to 0.94). There are still issues with computing complexity, dataset scarcity, and speckle noise. Our suggested system combines federated learning with multi-modal imaging.In multiclass image segmentation problems, hybrid filtering and learning-based segmentation strategies perform noticeably better than conventional approaches, as shown by the analysis of ROC curves. In all classes, methods like AWMF in conjunction with ACM or RBF Neural Networks and ELM consistently provide reduced false positive rates and greater true positive rates. This demonstrates their exceptional capacity to manage challenging segmentation problems, confirming the value of combining cutting-edge machine learning models with pre- processing methods.

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