A Novel Deep Learning Algorithm for Thyroid Cancer Classification

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Abstract

Thyroid cancer is one of the most prevalent endocrine malignancies, and accurate detection through medical imaging plays a crucial role in early diagnosis and treatment planning. However, challenges such as noise, low contrast, and variability in ultrasound images hinder precise analysis. This study presents an optimized deep learning pipeline for thyroid cancer detection, incorporating advanced pre-processing, segmentation, and classification techniques. In this research, IncrptionV3 is used to classify the Thyroid Cancer. The dataset comprises 3 classes based on Kaggle dataset. Pre-processing is performed using a bilateral filter to reduce noise while preserving edge details and adaptive histogram equalization (AHE) to enhance contrast, improving the visibility of tumor regions. For segmentation, the deep learning-based SegNet model is employed to accurately delineate thyroid nodules from surrounding tissues, leveraging its encoder-decoder architecture for precise boundary detection. Finally, classification is conducted using pre-trained InceptionV3, a powerful convolutional neural network (CNN) known for its deep feature extraction capabilities, enabling accurate differentiation between benign and malignant nodules. The proposed framework enhances diagnostic accuracy by improving image quality, ensuring robust segmentation, and leveraging a state-of-the-art classification model. Experimental results using accuracy, precision, recall, F1-score and specificity achieved were 98.81%, 98.85%, 98.81%, 98.81% and 99.40%, respectively.

Keywords: Thyroid cancer, medical imaging, thyroid nodule, deep learning, convolutional neural network (CNN).

1. Introduction

Thyroid cancer is one of the most common endocrine malignancies, with a rising incidence worldwide due to improved diagnostic techniques and increased awareness. The thyroid gland, located at the base of the neck, plays a crucial role in regulating metabolism through hormone production [1]. While many thyroid nodules are benign, some can be malignant, necessitating early and accurate diagnosis to ensure effective treatment. Traditional diagnostic methods, such as fine-needle aspiration biopsy (FNAB) and ultrasound imaging, are widely used; however, these approaches are often subject to inter-observer variability and may lead to inconclusive results. As a result, the demand for more objective, automated, and accurate diagnostic tools has grown, leading to the exploration of advanced computational techniques for thyroid cancer detection [2].

Medical imaging, particularly ultrasound, CT, and MRI scans, plays a vital role in thyroid cancer diagnosis. However, these images often suffer from low contrast, noise, and variability in nodule appearance, making manual analysis challenging [3]. Additionally, distinguishing between benign and malignant nodules based on imaging alone can be difficult, requiring expertise and extensive experience. To address these challenges, artificial intelligence (AI) and deep learning techniques have gained significant attention as powerful tools for enhancing image analysis, improving diagnostic accuracy, and reducing subjectivity. By leveraging vast amounts of imaging data, deep learning models can learn intricate patterns and provide reliable assessments, assi2sting radiologists in early thyroid cancer detection and decision-making [4].

Despite advancements in thyroid cancer diagnosis, several research gaps remain. Current imaging techniques, such as ultrasound and MRI, often struggle with low contrast, noise, and overlapping tissue structures, making accurate detection of malignant nodules challenging [5]. Traditional diagnostic approaches, including fine-needle aspiration biopsy (FNAB), sometimes yield indeterminate results, leading to unnecessary surgeries or missed diagnoses [6]. While deep learning and image processing methods have shown promise, there is a need for more robust, interpretable, and generalized models that can handle diverse patient populations and imaging variations. Additionally, integrating multi-modal data (e.g., combining ultrasound with genetic markers or clinical history) could significantly enhance classification accuracy [7]. Addressing these gaps can improve early detection, reduce false positives/negatives, and lead to more effective, personalized treatments for thyroid cancer patients.

- The study applies Bilateral Filtering to reduce noise while preserving important edges in thyroid ultrasound and MRI images. Additionally, Adaptive Histogram Equalization (AHE) enhances local contrast, making subtle differences between normal and cancerous tissues more distinguishable.
- A deep learning-based SegNet model is employed for precise segmentation of thyroid nodules, enabling pixel-wise classification of cancerous and non-cancerous regions.
- The study integrates pre-trained InceptionV3, a powerful convolutional neural network (CNN), for classifying segmented thyroid nodules into benign or malignant categories.
- An end-to-end pipeline integrates all processes from pre-processing to classification to enhance diagnostic accuracy and dependability in the evaluation of osteosarcoma.

The rest of this paper is organized as follows: Sect. 2 discusses the related works. The study methodology is given in Sect. 3 and Sect. 4 presents study results and discussion. In the end, Sect. 5 concludes this study

2. Literature Survey

Thyroid cancer detection has been an active area of research, with numerous studies focusing on improving diagnostic accuracy through imaging techniques, computational models, and artificial intelligence (AI)-based approaches. Traditional diagnostic methods, such as fine-needle aspiration biopsy (FNAB) and ultrasound imaging, have long been the gold standard for detecting thyroid malignancies. However, studies have shown that FNAB can sometimes yield indeterminate or inconclusive results, leading to unnecessary surgeries or missed diagnoses. To improve non-invasive diagnostic accuracy, researchers have explored various machine learning and deep learning techniques for automated thyroid nodule detection and classification. These advancements aim to minimize human errors and provide more objective, reproducible, and efficient diagnostic outcomes [8].

Several studies have focused on image pre-processing techniques to enhance thyroid ultrasound images before applying automated analysis. Noise reduction methods such as bilateral filtering and speckle noise reduction algorithms have been widely used to improve image clarity [9]. Additionally, contrast enhancement techniques, including adaptive histogram equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), have been explored to make subtle features within the thyroid gland more distinguishable. Studies have demonstrated that pre-processing techniques significantly improve nodule segmentation accuracy, leading to better feature extraction and classification performance. These findings emphasize the importance of high-quality input images for accurate thyroid cancer detection [10].

In the field of segmentation, deep learning models such as U-Net, SegNet, and Mask R-CNN have been extensively studied for thyroid nodule boundary detection [11]. Research indicates that SegNet, with its encoder-decoder architecture, performs well in segmenting thyroid nodules from ultrasound images by accurately preserving boundary details. Several comparative studies have shown that deep learning-based segmentation techniques outperform traditional thresholding and edge-detection methods, which often struggle with low-contrast images and complex nodule structures. The success of these segmentation models has paved the way for improved automated thyroid cancer detection systems, reducing dependence on manual delineation by radiologists [12].

For classification, studies have explored various CNN architectures, such as VGG16, ResNet, and InceptionV3, to differentiate benign and malignant thyroid nodules. Research has shown that InceptionV3, due to its ability to perform multi-scale feature extraction, achieves high accuracy in distinguishing between different types of thyroid lesions [13]. Additionally, studies incorporating transfer learning and data augmentation have reported significant improvements in model performance, especially when dealing with limited thyroid imaging datasets [14]. Furthermore, hybrid AI approaches, such as combining deep learning with clinical features like nodule size, echogenicity, and vascularity, have shown promising results in enhancing the diagnostic reliability of AI-assisted thyroid cancer detection systems. These advancements highlight the growing role of deep learning in transforming thyroid cancer diagnosis, reducing false positives, and improving early detection rates [15].

3. Methodology

A systematic approach is implemented to enhance medical image analysis, starting with pre-processing, followed by segmentation and classification. Initially, Bilateral filter and Adaptive Histogram Equalization were employed to enhance image quality, effectively reduce noise, and intensify critical features crucial for accurate segmentation. The segmentation phase utilizes the SegNet, a model specifically developed, facilitating the precise segmentation of healthy and cancer. Following segmentation, the pre-trained InceptionV3 is implemented for classification, harnessing self-attention mechanisms to analyze spatial and contextual relationships and accurately distinguish between healthy and diseased tissues. The overall proposed architecture as shown in Figure 1.

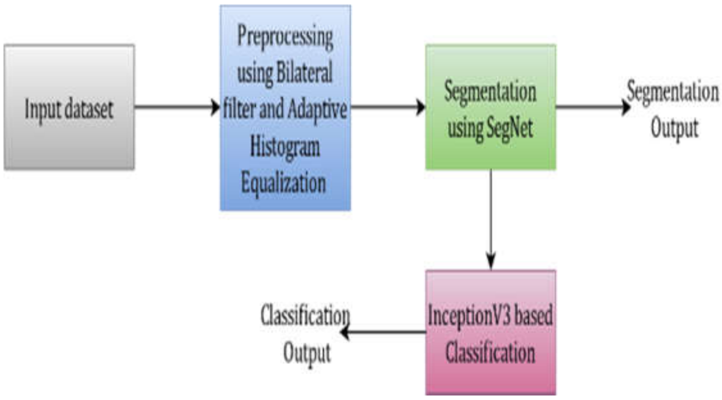

Figure 1: Overall Proposed architecture

3.1 Dataset

We imported this data from Algeria's hospitals exactly Setif city, and it was labeled by volunteer doctors. the dataset contains 3 classes: Benign with 1,472 ultrasound image and Malignant with 1,895 ultrasound image, Normal thyroid 171 with ultrasound image. [https://www.kaggle.com/datasets/azouzmaroua/algeria-ultrasound-images-thyroid-dataset-auitd]

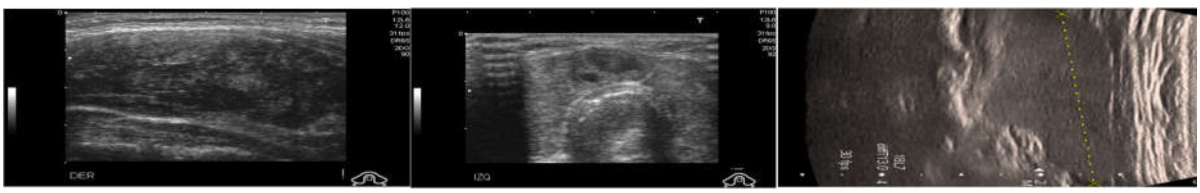

Figure 2: Sample images

3.2 Pre-Processing

Pre-processing is a crucial step in medical image analysis that enhances image quality by reducing noise, improving contrast, and standardizing features before further processing. It ensures that images are more suitable for segmentation, and classification.

3.2.1 Bilateral Filtering

A bilateral filter is a nonlinear, edge-preserving, and noise-reducing smoothing filter commonly used in medical imaging, including thyroid cancer detection. It works by averaging nearby pixels while maintaining sharp edges, making it ideal for enhancing ultrasound and CT scan images where preserving tumor boundaries is crucial. In thyroid cancer imaging, the bilateral filter helps in reducing speckle noise while retaining important structural details of the thyroid gland and nodules. This leads to improved segmentation and diagnosis accuracy, aiding radiologists in detecting cancerous regions more effectively.

Mathematically, the bilateral filter is expressed as:

$$I'(x) = \frac{1}{W_p} \sum_{x_i \epsilon \Omega} I(x_i) \cdot G_s\left(\left||x_i - x|\right|\right) \cdot G_r(|I(x_i) - I(x)|) \qquad (1)$$

where $I'(x)$ is the filtered intensity at pixel x, $I(x_i)$ represents the intensity of neighboring pixels within a window Ω and W_p is a normalization factor given by $W_p = \sum_{x_i \epsilon \Omega} I(x_i) \cdot G_s\left(\left||x_i - x|\right|\right) \cdot G_r(|I(x_i) - I(x)|)$. The spatial Gaussian function $G_s(\| x_i - x \|)$ controls the influence of nearby pixels based on their spatial distance, while the range Gaussian function $G_r(| I(x_i) - I(x) |)$ controls the influence based on intensity differences, preserving edges in the image.

3.2.2 Adaptive Histogram Equalization (AHE)

Adaptive Histogram Equalization (AHE) is an advanced image enhancement technique widely used in medical imaging, including thyroid cancer diagnosis. Unlike traditional histogram equalization, which applies a uniform contrast enhancement across the entire image, AHE enhances local contrast by considering smaller regions, making it particularly effective in highlighting subtle differences in thyroid tissue. This is crucial in ultrasound and MRI scans, where fine details of malignant and benign nodules need to be distinguished clearly. By improving contrast adaptively, AHE enhances the visibility of critical structures, aiding radiologists in more accurate tumor detection and assessment.

Mathematically, AHE works by computing the transformation function for each pixel based on its local neighborhood. Given an image $I(x, y)$, the transformation function is derived from the local cumulative distribution function (CDF), defined as:

$$T(I) = \frac{CDF(I) - CDF_{min}}{(M \times N) - CDF_{min}} \times (I_{max} - I_{min}) \qquad (2)$$

where $CDF(I)$ is the cumulative histogram of the pixel intensities within a defined local window of size $M \times N$, CDF_{min} is the minimum nonzero value of the CDF, and I_{max} and I_{min} are the maximum and minimum intensity values in the window. This transformation is applied independently to different regions of the image, ensuring that local contrast variations are effectively enhanced without over-amplifying noise.

In thyroid cancer imaging, Contrast Limited Adaptive Histogram Equalization (CLAHE) is preferred over AHE to prevent noise amplification in uniform areas. By setting a clip limit, CLAHE enhances contrast while preserving thyroid tissue texture and improving the visibility of suspicious nodules, leading to better diagnostic accuracy in ultrasound and MRI scans.

Bilateral filtering and histogram equalization are also commonly used to refine medical images before analysis. The bilateral filter smooths noise while preserving edges, ensuring clear tumor boundaries. Unlike Gaussian filters, it considers both spatial and intensity differences to maintain structural details. Adaptive histogram equalization enhances contrast by redistributing pixel intensity, making subtle abnormalities more visible.

These pre-processing techniques improve segmentation, feature extraction, and classification, helping radiologists and diagnostic models detect thyroid cancer more accurately. Figure 3 compares original and pre-processed thyroid tissue images.

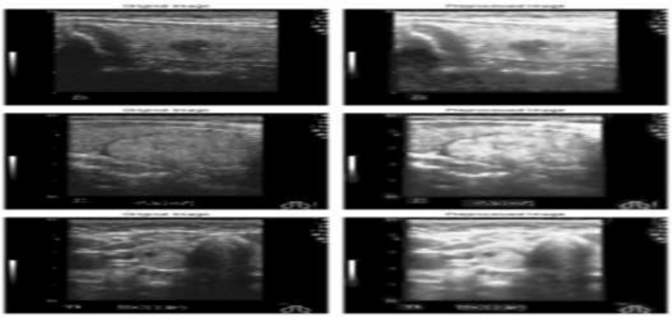

Figure 3: Pre-Processing result for Thyroid Cancer

3.3 Segmentation by SegNet networks

The semantic segmentation model in Figure 3 processes full-size images end-to-end for feature extraction. It uses a pretrained SegNet, fine-tuned with manually annotated tumor regions. During testing, the trained SegNet generates tumor segmentation masks for new images.

SegNet is preferred over DeconvNet for its lower computational needs and over U-Net for its memory efficiency, as it reuses pooling indices instead of entire feature maps. The architecture replaces VGG-16's fully connected layers with convolutional layers, reducing encoder parameters from 134 million to 14.7 million while preserving spatial information.

SegNet follows an encoder-decoder structure with 13 convolutional layers in both paths. The encoder has five convolutional blocks with 3 × 3 convolutions, batch normalization, and ReLU activation. Max-pooling (2 × 2, stride 2) downsamples the feature maps, and the decoder symmetrically replaces max-pooling with upsampling using stored pooling indices. The final output is passed through a softmax classifier, producing pixel-wise segmentation probabilities for K target classes (Figure 4).

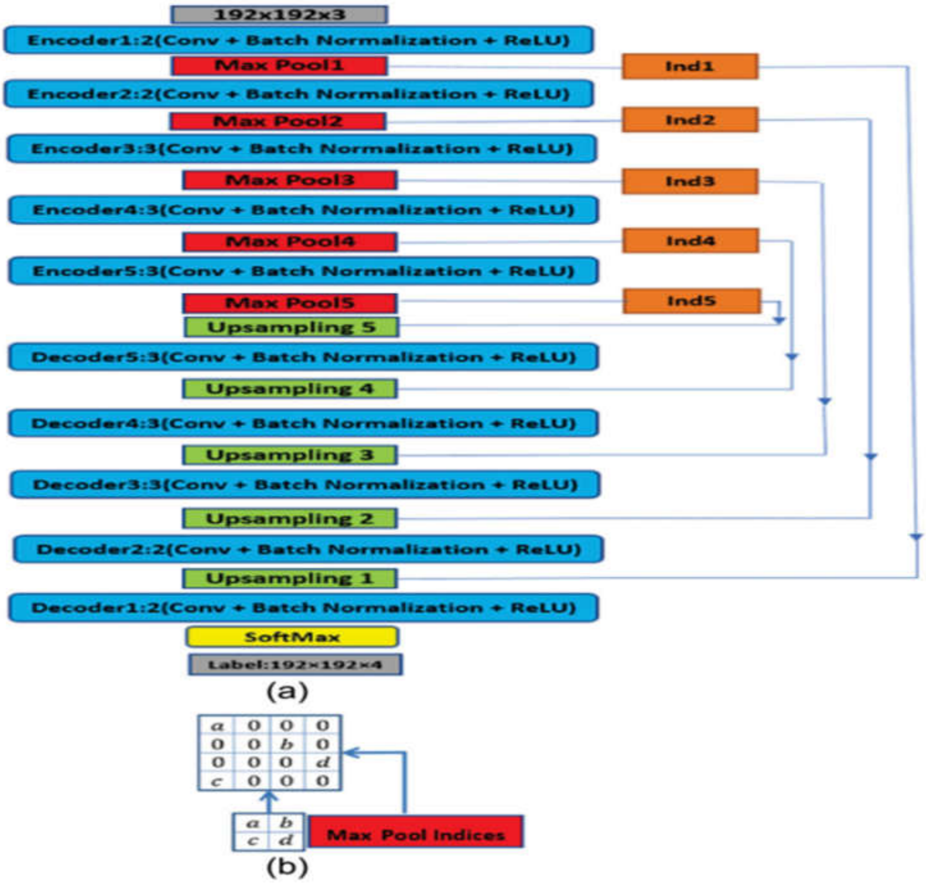

Figure 4: (a) Architecture of the SegNet; (b) SegNet which uses max pooling indices to up-sample the feature maps and convolve them with a trainable decoder filter bank.

The core of SegNet lies in its encoder-decoder structure, which processes an input image II of size H×W×CH (Height, Width, Channels) through a series of convolutional and max-pooling layers. Mathematically, the encoder operation can be expressed as:

$$X^l = f(W^l * X^{l-1} + b^l) \qquad (3)$$

Where X^l is the feature map at layer W^l, f^l *and* b^l represent the weight and bias of the convolutional filter, $*^*$ denotes convolution, $f(\cdot)$is a non-linear activation function (typically ReLU).

The max-pooling operation in SegNet reduces spatial dimensions while retaining important features, expressed as:

$$P(x,y) = \max_{x' \epsilon R_x y' \epsilon R^y} X^l(x',y') \qquad (4)$$

where $P(x,y)$ represents the pooled value over the receptive field $Rx \times Ry$. Unlike conventional decoders, SegNet's decoder upsamples using the saved indices from the max-pooling step instead of learning additional parameters, ensuring efficient reconstruction:

$$U(x,y) = X^l\left(I_p(x,y)\right) \qquad (5)$$

where $I_p(x,y)$ are the stored pooling indices. The final segmentation map is obtained by applying a softmax activation function, converting feature maps into class probabilities for each pixel:

$$P(c|X) = \frac{e^{Xe}}{\sum_j e^{Xj}} \qquad (6)$$

where $P(c \mid X)$ represents the probability of class c (cancerous or non-cancerous) given the input features X.

SegNet is trained using a large dataset of thyroid ultrasound or MRI images labeled with cancerous and non-cancerous regions. The loss function typically used is categorical cross-entropy for multi-class segmentation or Dice loss for handling imbalanced data, given as:

$$\mathcal{L}_{Dice} = 1 - \frac{2\sum(P_i T_i)}{\sum P_i + \sum T_i} \qquad (7)$$

where $P_i\ and\ T_i$ are the predicted and true pixel values. The model is optimized using an adaptive optimization algorithm such as Adam or SGD. SegNet's precise segmentation helps in automating thyroid cancer detection, enabling radiologists to identify suspicious nodules with greater accuracy, reducing misdiagnosis, and improving patient outcomes. The integration of SegNet with computer-aided diagnosis (CAD) systems enhances the reliability of thyroid cancer screening, making it a powerful tool for real-world clinical applications.

3.4 InceptionV3 based Classification

After pre-processing and segmentation, the next critical stage in the pipeline is classification, where the segmented thyroid nodule is analyzed to determine whether it is benign or malignant. This step is essential for accurate diagnosis and effective treatment planning. Deep learning-based classification models, such as convolutional neural networks (CNNs), have shown remarkable success in medical image classification by learning complex patterns that may not be easily discernible to the human eye. The pre-trained InceptionV3 model, in particular, is chosen for this study due to its ability to efficiently extract high-level features, making it highly suitable for medical imaging applications. The classification process begins with feeding the segmented and pre-processed thyroid images into the pre-trained InceptionV3 model, which then learns to differentiate between benign and malignant nodules based on extracted features such as texture, shape, and intensity variations.

InceptionV3 is a deep convolutional neural network that has been widely used in image recognition tasks, including medical image analysis. Unlike traditional CNNs, which rely on fixed-sized filters, pre-trained InceptionV3 utilizes multi-scale feature extraction, allowing it to capture both fine and coarse details in thyroid nodules. This is particularly beneficial in thyroid cancer detection, where nodules vary significantly in size, shape, and texture. The model's architecture is designed to improve computational efficiency while maintaining high accuracy. By using factorized convolutions and asymmetric convolutions, pre-trained InceptionV3 reduces the number of parameters, making training faster and preventing overfitting. Furthermore, the inclusion of batch normalization helps stabilize the training process and improves generalization across different datasets. These architectural improvements enable pre-trained InceptionV3 to achieve superior performance in distinguishing between benign and malignant thyroid nodules compared to conventional CNNs.

To further improve classification accuracy and ensure robustness in real-world applications, pre-trained InceptionV3 employs global average pooling (GAP) instead of fully connected layers. GAP reduces the risk of overfitting by averaging feature maps instead of using a large number of trainable parameters. Additionally, transfer learning is often used, where a pre-trained pre-trained InceptionV3 model (trained on large-scale datasets like ImageNet) is fine-tuned on a thyroid-specific dataset. This approach significantly enhances the model’s performance, especially when dealing with limited medical image datasets. Furthermore, data augmentation techniques, such as rotation, flipping, and contrast adjustments, are applied to improve generalization and reduce model bias. Given the variability in ultrasound images due to different scanning conditions, patient anatomy, and image quality, these strategies ensure that the model remains robust and adaptable across different clinical scenarios. By leveraging the advanced capabilities of pre-trained InceptionV3, the classification model effectively identifies thyroid malignancies with high precision, aiding radiologists in early diagnosis and improving patient outcomes.

4. Results and Discussion

This research utilized Python version 3.8, along with powerful deep learning frameworks such as PyTorch 1.10 and TensorFlow 2.6, for effective model development and optimization. Data manipulation and analysis were performed using Pandas 1.3.3, NumPy 1.21.2, with visual representations crafted using Matplotlib 3.4.3, and Seaborn 0.11.2. The computational environment was supported by a high-performance workstation featuring an NVIDIA RTX 3090 GPU with 24GB VRAM, 64GB DDR4 RAM, and an Intel Core i9-11900K processor, specifically tailored to handle intensive calculations and large data volumes. The parameters and values used in the process are listed in Table.2. This setup enables efficient model training, validation, and performance assessment, thereby enhancing the overall research process.

Segmentation results for thyroid cancer tissue samples, comparing original images, mask images, and segmented outputs, each annotated with the Dice coefficient. The model demonstrates a highly accurate segmentation performance, which highlights its precision in identifying cancerous regions. These high coefficients, displayed alongside each segmented image, signify the effectiveness of the model in closely matching the predicted regions with the actual cancer areas, as illustrated in Figure 5.

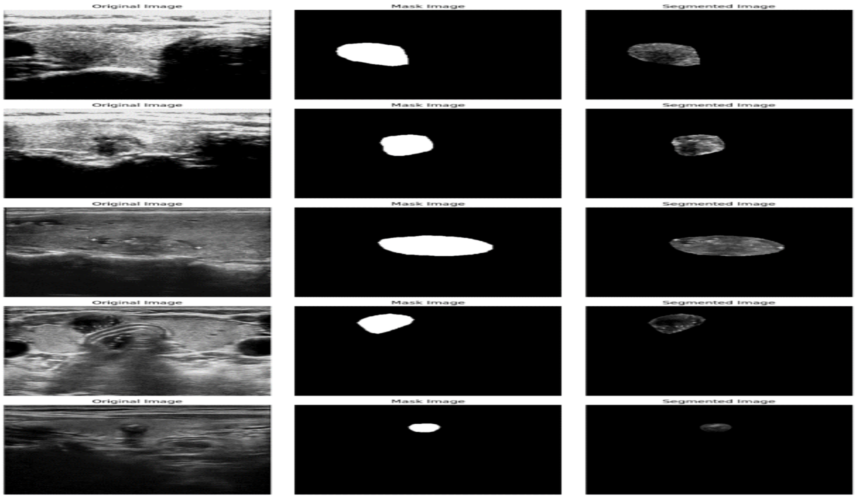

Figure 5: Original, Mask, and Segmented Images for thyroid Cancer Dataset

The confusion matrix of a proposed classification model was applied to the thyroid cancer dataset to distinguish between "Normal Thyroid", "True Label benign" and "Malignant" categories. The model correctly identified 100% of Malignant cases, with a minimal misclassification rate of 0% as true label benign and 0% as normal thyroid, reflecting high accuracy in malignant case identification. Similarly, true label benign cases were classified with 96.43% accuracy, showing only slight errors with 3.57% misclassified as malignant and 0% as normal thyroid, as illustrated in Figure 6. Normal Thyroid cases achieved a perfect classification rate of 100%, underscoring the reliability of the model across all classes.

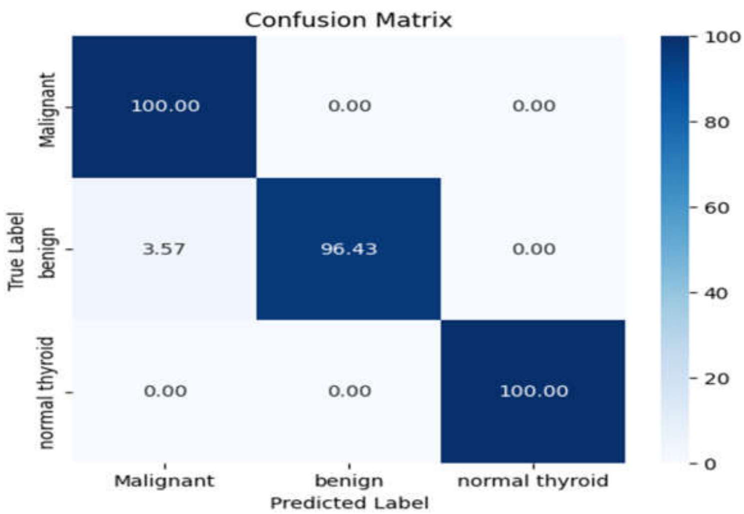

Figure 6: Confusion Matrix for classification of thyroid cancer dataset

The training and validation curves in Figure 7 display the accuracy and loss progression over 30 epochs for the classification of the thyroid cancer dataset. As the training progressed, the model achieved an overall accuracy of 98.8% and a minimal loss of 1.0020, indicating strong learning efficiency. In the accuracy graph, the model shows rapid improvement within the first 10 epochs, with the validation accuracy aligning closely with the training accuracy after an initial rise, suggesting a well-generalized performance. The loss curves revealed a consistent decline, stabilizing near zero as epochs proceeded, underscoring effective model convergence with minimal overfitting.

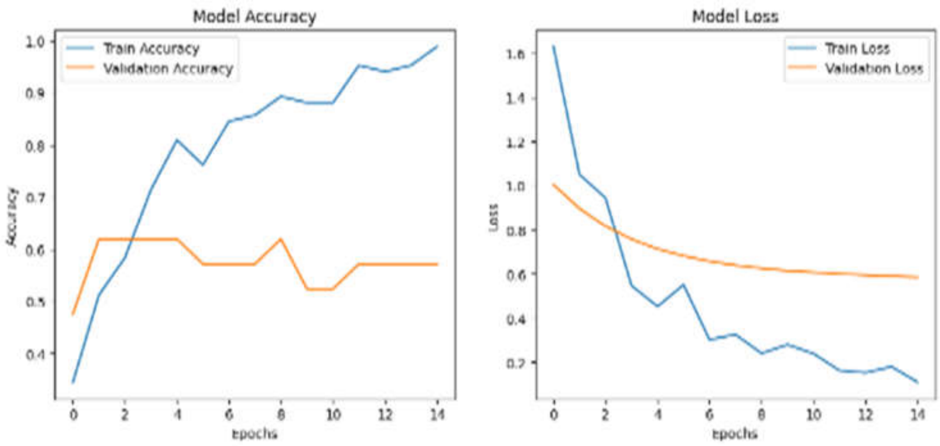

Figure 7: Training and Validation Accuracy and Loss for Thyroid Cancer Dataset

The bar chart in Figure 8 presents the performance metrics for the classification model applied to the thyroid cancer dataset, with an accuracy, precision, recall, F1-score, and specificity of approximately 98.81%. These nearly identical values across all metrics highlight the balance and effectiveness of the model in handling the complexities of classification. Specifically, a precision of 98.85% and recall of 98.81% indicate the model's capability to minimize both false positives and false negatives, ensuring reliable identification of each class.

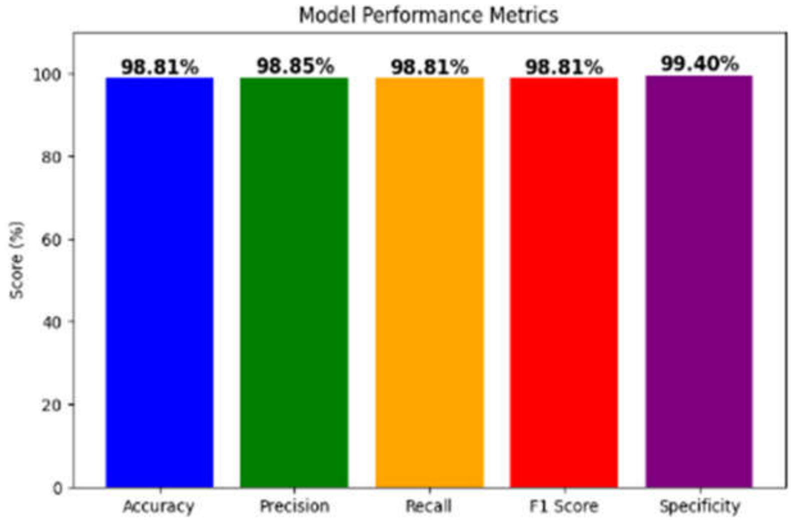

Figure 8: Performance Metrics of Classification of Bone Cancer Dataset

The model classification performance for the "Malignant", "True Label Benign", and "Normal Thyroid" classes within the thyroid-cancer datasets. The Area Under the Curve (AUC) values are 1.00 for malignant, 1.00 for true label benign, and 1.00 for normal thyroid, reflect a high degree of accuracy across all classes. These values, which are situated well above the chance line, indicate the model's strong capability to differentiate between classes with minimal classification, as shown in Figure 9. The highest AUC for the true label benign class suggests that the model performs particularly well in identifying true label benign cases while maintaining high accuracy for malignant and normal thyroid categories.

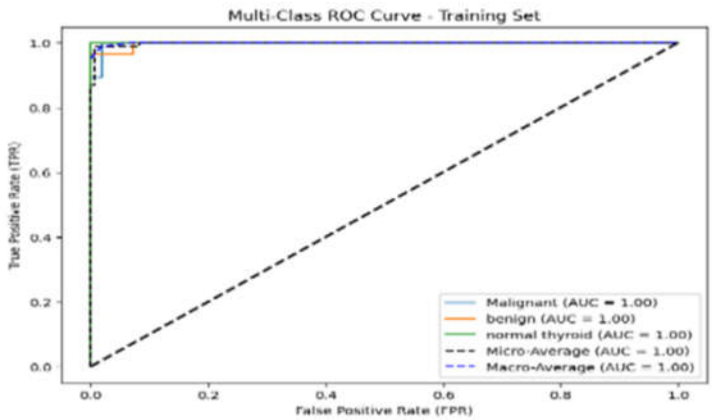

Figure 9: ROC Curve for Classification of Bone Cancer Dataset

5. Conclusion

Thyroid cancer classification using pre-trained InceptionV3 is a highly effective deep learning approach that leverages advanced feature extraction to distinguish between malignant and benign thyroid nodules. By utilizing a deep convolutional network with multiple filter sizes, pre-trained InceptionV3 efficiently captures both fine-grained and high-level features, improving classification accuracy. However, to achieve optimal performance, high-quality input images are essential, making pre-processing a crucial step in the pipeline. Pre-processing techniques such as the Bilateral Filter and Adaptive Histogram Equalization (AHE) play a significant role in enhancing thyroid ultrasound or MRI images. The Bilateral Filter smooths noise while preserving important edges, ensuring that critical structures such as nodule boundaries remain intact. Meanwhile, AHE enhances local contrast, improving the visibility of subtle differences between normal and cancerous tissue. Together, these techniques provide a cleaner and more informative input for both segmentation and classification models, improving overall diagnostic accuracy. For precise localization of thyroid nodules, SegNet is employed as the segmentation model, effectively delineating cancerous regions with pixel-level accuracy. By using an encoder-decoder architecture with max-pooling indices, SegNet ensures minimal information loss while achieving high segmentation performance. The segmented regions serve as refined inputs for the classification model, further boosting pre-trained InceptionV3's ability to distinguish thyroid cancer cases. The combination of pre-processing, segmentation, and deep learning classification creates a robust pipeline that enhances diagnostic efficiency, reduces false positives and negatives, and ultimately aids in the early and accurate detection of thyroid cancer, improving patient outcomes. Using classification of pre-trained InceptionV3 improves the overall accuracy of 98.81%, precision of 98.85%, recall of 98.81%, f1-score of 98.81% and specificity of 99.40%. Future research can enhance thyroid cancer detection by developing more robust, interpretable, and real-time deep learning models with multi-modal data integration.

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