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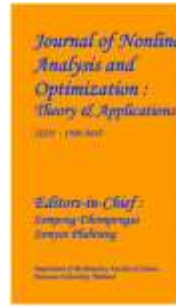

Improved YOLOv5 Neural Network for Automatic Thyroid Nodule Detection in Ultrasound Imaging

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Abstract: In order to improve accuracy and efficiency in cancer diagnosis, this work incorporates advanced YOLO models, such as YOLOv5x6, YOLOv8, and YOLOv9, into thyroid nodule identification in ultrasound imaging. By utilising improved feature extraction techniques, the network obtains greater lesion recognition and classification. Additionally, the Flask framework was used to create an intuitive web-based interface that integrated authentication to guarantee safe access to medical data. By offering a more accurate and user-friendly diagnostic tool, the expanded system lowers the possibility of misdiagnosis while preserving effectiveness and scalability for upcoming developments in sonographic analysis.

Index Terms— Thyroid Nodule Detection, Ultrasound Imaging, YOLOv5x6, YOLOv8, YOLOv9, Deep Learning, Computer-Aided Diagnosis, Medical Image Analysis, Flask Framework, Secure Authentication, Sonographic Cancer Detection.

1. INTRODUCTION

Adults frequently have thyroid nodules, which are frequently early signs of thyroid cancer. Over the past few decades, thyroid cancer has become much more common, which has raised the pressure on radiologists to make accurate diagnoses. The principal non-invasive and economical technique for finding thyroid nodules is still ultrasonography. However, conventional ultrasound-based diagnosis is subject to subjectivity and misdiagnosis because it mostly depends on radiologists' competence. Thyroid nodule intricacy, tiny size, and hazy boundaries make diagnosis even more difficult. Furthermore, the pricey and invasive fine-needle aspiration biopsy (FNAB), which is frequently employed as a secondary confirmation procedure, may still leave 10–30% of nodules unclear. An effective automated approach is therefore desperately needed to improve diagnostic precision and cut down on pointless FNAB procedures.

Convolutional neural networks (CNNs) and other deep learning-based object detection methods have greatly enhanced medical picture analysis. Ultrasound image analysis has showed promise using YOLO (You Only Look Once) models, which are renowned for their real-time detection capabilities. In order to increase the accuracy and effectiveness of thyroid nodule identification, we expand on the earlier YOLOv5-based method in this work by using sophisticated YOLO models, such as YOLOv5x6, YOLOv8, and YOLOv9. By improving feature extraction and classification, these models improve the ability to distinguish between benign and malignant nodules.

The Flask framework was also used to create an intuitive web-based interface that allowed for easy interaction with the detection model. The system is appropriate for clinical deployment since it includes authentication procedures to guarantee safe access to medical data. The suggested method seeks to offer a dependable, scalable, and effective diagnostic solution for thyroid cancer detection by utilising cutting-edge YOLO models and a safe, easily accessible platform, lowering the rate of misdiagnosis and enhancing patient outcomes.

2. LITERATURE SURVEY

a) A Novel Model of Thyroid Nodule Segmentation for Ultrasound Images:

https://www.sciencedirect.com/science/article/abs/pii/S0301562922005774

ABSTRACT: Thyroid nodule detection, diagnosis, and monitoring are effective with ultrasonography. Ultrasound thyroid nodule segmentation is crucial in clinical practice. Ultrasound pictures provide an imprecise boundary between thyroid nodules and surrounding tissues, making segmentation difficult. The deep learning model segments thyroid nodules accurately and conveniently, but it fails to segment the margin. In this study, we built boundary attention transformer net (BTNet), a novel segmentation network with a boundary attention mechanism that combined convolutional neural network with transformer advantages to fuse long and short range information. This module improves network border segmentation by focussing boundary attention on learning boundary information. We also use deep supervision to combine outputs from multiple scales to improve segmentation. Our model segments thyroid nodules well because the BTNet model integrates the long range–short range connection impact and boundary–regional cooperation. BTNet was developed using Shanghai Jiao Tong University School of Medicine Affiliated Sixth People's Hospital and public data. BTNet segmented thyroid nodules well with an intersection-over-union of 0.810 and Dice coefficient of 0.892. Additionally, our approach showed significant improvements in boundary measures, such as 7.308 for distance, 0.201 for overlap, and 0.194 for dice, all with p values <0.05.

b) Improving GAN Learning Dynamics for Thyroid Nodule Segmentation:

https://www.sciencedirect.com/science/article/abs/pii/S0301562922005695

ABSTRACT: Thyroid nodules need diagnosis and monitoring. Nodule detection and segmentation tools can assist doctors diagnose this. In addition to fast diagnosis, automated techniques can track malignancy risk over time. This research presents a new ultrasound thyroid nodule segmentation algorithm. We use GANs to combine supervised semantic segmentation with unsupervised learning. The hybrid technique could improve the semantic segmentation model, although GANs have unstable learning and mode collapse. We use closed-loop gain control on the discriminator loss output to stabilise GAN model training. Gain control smoothes generator training and prevents mode collapse when the discriminator learns too fast relative to the generator. We also find that supervised and unsupervised learning styles promote poor accuracy and high consistency. StableSeg GAN is a new model that tests controlled hybrid supervised and unsupervised semantic segmentation. The model uses DeeplabV3+ to generate, Resnet18 to discriminate, and PID control to stabilise GAN learning. The new model outperforms DeeplabV3+ with a mean IoU of 81.26% on a difficult test set. Our thyroid nodule segmentation studies reveal that StableSeg GANs can segment nodules more correctly than equivalent supervised segmentation models or uncontrolled GANs.

c) Automated thyroid nodule detection from ultrasound imaging using deep convolutional neural networks:

https://www.sciencedirect.com/science/article/abs/pii/S0010482520302262

ABSTRACT: The prevalence of thyroid cancer, the most prevalent endocrine malignancy, has been steadily rising globally. The difficult issue of nodule recognition using ultrasound scans is the main emphasis of this paper. This task is currently completed manually in clinical practice, which is time-consuming, subjective, and heavily reliant on radiologists' clinical expertise. In order to accomplish nodule recognition without the need for intricate post-processing refinement processes, we suggest a novel deep neural network architecture with carefully crafted loss function regularisation and network hyperparameters. 2461 and 820 ultrasound frames obtained from 60 and 20 patients with a significant degree of variability make up the local training and validation datasets, respectively. A deep learning framework based on the multi-task model Mask R-CNN forms the basis of the suggested approach. We have created a regularised loss function that gives detection precedence over segmentation. Validation was done on 20 patients' 821 ultrasound frames. The suggested model is capable of identifying different kinds of thyroid nodules. The experimental findings show that our suggested approach is successful in detecting thyroid nodules. The suggested model performs better than the previous state-of-the-art detection techniques, as shown by comparisons with the outcomes of Faster R-CNN and traditional Mask R-CNN.

d) Efficient Deep Learning Architecture for Detection and Recognition of Thyroid Nodules:

https://onlinelibrary.wiley.com/doi/full/10.1155/2020/1242781

ABSTRACT: Thyroid nodule clinical diagnosis frequently involves ultrasound. Because of their varied looks, internal characteristics, and hazy borders, thyroid nodule ultrasound images make it challenging for doctors to distinguish between benign and malignant forms based only on visual recognition. Medical image diagnosis has advanced significantly as a result of the development of artificial intelligence, particularly deep learning. To identify thyroid nodules accurately and efficiently, there are several obstacles to overcome. We present a deep learning architecture based on YOLOv3 called the You Only Look Once v3 Dense Multireceptive Fields Convolutional Neural Network (YOLOv3-DMRF). It consists of multiscale detection layers and a DMRF-CNN. We continue to pass the edge and texture characteristics to further layers in DMRF-CNN by integrating dilated convolution with varying dilation rates. To identify the various sizes of the thyroid nodules, two distinct scale detection layers are used. Throughout the studies, we trained and assessed the YOLOv3-DMRF using two datasets. 699 original ultrasound pictures of thyroid nodules taken from a nearby health facility are included in one dataset. After data augmentation, we were able to collect 10,485 pictures. An additional publicly available dataset consists of ultrasound pictures of 41 benign and 111 malignant thyroid nodules. Metrics for both quantitative and qualitative assessments are mean average precision (mAP) and average precision (AP). The suggested YOLOv3-DMRF was contrasted with a few cutting-edge deep learning networks. According to the experimental findings, YOLOv3-DMRF performs better than the others on both datasets in terms of mAP and detection time. In particular, on the two test datasets, the mAP and detection time values were 90.05 and 95.23% and 3.7 and 2.2 s, respectively. The suggested YOLOv3-DMRF is effective in detecting and identifying thyroid nodules on ultrasound images, according to experimental data.

e) Patch-based classification of thyroid nodules in ultrasound images using direction independent features extracted by two-threshold binary decomposition:

https://www.sciencedirect.com/science/article/abs/pii/S0895611118301915

ABSTRACT: Thyroid gland ultrasound imaging is thought to be the most cost-effective, non-invasive, and risk-free diagnostic option for assessing thyroid nodules in their early stages. By providing radiologists with a second opinion, computer-aided diagnosis (CAD) systems can improve the overall diagnostic precision of ultrasound imaging. Despite showing encouraging outcomes, modern CAD systems are not widely used in clinical practice. Some of the primary drawbacks include the fact that most of them rely on direction-dependent features, which means they can only be used with static images in one plane (axial or longitudinal), necessitating accurate nodule segmentation. Our goal was to create a CAD system that used solely direction independent features—that is, one that was not reliant on the orientation or inclination angle of the ultrasonic probe at the time of image acquisition. Using Two-Threshold Binary Decomposition, a technique that breaks down an image into a group of binary pictures, 60 thyroid nodules (20 malignant, 40 benign) were separated into tiny patches of 17 × 17 pixels. These patches were then utilised to extract many direction-independent features. The nodules were then divided into benign and malignant classifications using Random Forests (RF) and Support Vector Machine (SVM) classifiers based on the characteristics. Group 10-fold cross-validation was used to assess classification. The classification of entire nodules was subsequently achieved by averaging performance on separate patches, yielding the following outcomes: overall accuracy, sensitivity, specificity, and area under the receiver operating characteristics (ROC) curve: For RF, it was 95%, 95%, 95%, 0.971, while for SVM, it was 91.6%, 95%, 90%, 0.965. By improving the overall accuracy of ultrasound imaging, the patch-based CAD method we offer can assist radiologists in their current thyroid nodule diagnosis.

3. METHODOLOGY

Through the integration of sophisticated YOLO models (YOLOv5x6, YOLOv8, and YOLOv9), the suggested system improves thyroid nodule detection for increased efficiency and accuracy in ultrasound image processing. In order to improve lesion detection and classification through improved feature extraction, the models are trained using a dataset of thyroid ultrasound images. While Label Smoothing Regularisation (LSR) reduces overfitting, the Coordinate Attention (CA) module enhances positional information. For easy use, a Flask-based web interface with authentication is created for safe management of medical data. This solution maintains a scalable and secure diagnostic platform while guaranteeing accurate, real-time detection.

A. Proposed Work:

In order to improve ultrasound imaging accuracy and efficiency, we present in this extended study a sophisticated thyroid nodule detection system that makes use of cutting-edge YOLO models, such as YOLOv5x6, YOLOv8, and YOLOv9. By utilising improved feature extraction and real-time processing capabilities, these models enhance lesion recognition and classification. Positional awareness is improved by integrating the Coordinate Attention (CA) module, and model robustness is increased and overfitting is decreased using Label Smoothing Regularisation (LSR).

A web-based interface is created utilising the Flask framework to provide practical usability, giving medical practitioners an easy-to-use platform. User authentication is incorporated into the system to guarantee safe access and safeguard private medical information. The suggested method reduces misdiagnosis and needless fine-needle aspiration biopsies (FNAB) by providing a quicker, more accurate, and scalable thyroid nodule detection approach. It is also a useful tool for clinical applications because of its adaptable architecture, which enables the smooth incorporation of upcoming deep learning developments.

B. System Architecture:

Extended thyroid nodule detection system architecture uses modern deep-learning models to effectively process ultrasound pictures while ensuring safe and user-friendly access. The design begins with thyroid ultrasound image acquisition and preprocessing for visibility and detection accuracy. The model training process trains state-of-the-art YOLO models like YOLOv5x6, YOLOv8, and YOLOv9 on labelled datasets using these photos. Coordinate Attention (CA) improves the network's spatial and contextual information extraction, while Label Smoothing Regularisation (LSR) reduces overfitting and makes the model more resilient to misclassified training samples.

Once trained, the system detects and classifies thyroid nodules in real time, distinguishing benign from malignant. An straightforward Flask-based web interface lets doctors upload ultrasound photos and get quick diagnostic findings. Data privacy is protected by authentication procedures that limit access to authorised users. Lesion localisation and classification findings are safely kept for future examination. Modularity offers scalability and future upgrades, allowing smooth incorporation of updated deep-learning models and diagnostic features. High accuracy, rapid processing speeds, and safe access make this architecture useful for thyroid cancer detection clinical applications.

Fig proposed architecture

C. MODULES:

The proposed system is structured into several key modules to ensure efficient thyroid nodule detection and classification. Each module plays a crucial role in data processing, model training, prediction, and user interaction. The main modules are as follows:

i. **Data Acquisition and Preprocessing Module**

- Collects thyroid ultrasound images from medical sources.
- Applies preprocessing techniques such as noise reduction, contrast enhancement, and resizing to improve image quality for better model performance.
- Performs data augmentation (rotation, flipping, scaling) to increase the dataset's diversity and enhance model generalization.

ii. **Deep Learning Model Training Module**

- Implements advanced YOLO models (YOLOv5x6, YOLOv8, and YOLOv9) for training on labeled ultrasound datasets.
- Integrates Coordinate Attention (CA) module to improve feature extraction and spatial localization of thyroid nodules.
- Applies Label Smoothing Regularization (LSR) to reduce overfitting and improve model robustness.
- Fine-tunes hyperparameters to optimize detection accuracy and inference speed.

iii. **Nodule Detection and Classification Module**

- Processes input ultrasound images through the trained YOLO models.
- Detects thyroid nodules and classifies them as benign or malignant based on extracted features.
- Generates bounding boxes around detected nodules with confidence scores.
- Ensures real-time processing for quick and accurate diagnosis.

iv. **Web-Based User Interface Module**

- Developed using the Flask framework to provide a user-friendly web interface.
- Allows users (radiologists, healthcare professionals) to upload ultrasound images and receive detection results.
- Displays classification results, confidence scores, and lesion localization visually.

v. **Authentication and Security Module**

- Implements user authentication to ensure secure access to medical data.
- Protects patient confidentiality and prevents unauthorized access.
- Uses encryption and secure database storage for sensitive information.

vi. **Result Analysis and Storage Module**

- Stores detected results for future reference and medical review.
- Provides logs for model performance evaluation and potential improvements.

- Allows retrieval of past diagnoses for comparison and trend analysis.

D. Algorithms:

a) SSD: SSD is employed for real-time object detection, enabling rapid identification of thyroid abnormalities in ultrasound images. Its efficiency helps radiologists quickly assess potential cancerous regions during diagnosis.

b) RetinaNet: RetinaNet is utilized to address class imbalance in detection tasks, enhancing the accuracy of thyroid cancer identification. Its focal loss function helps improve detection performance of small and overlapping nodules.

c) FasterRCNN: FasterRCNN provides high accuracy in object detection by combining region proposal networks with deep learning. It efficiently identifies and classifies thyroid nodules, aiding radiologists in accurate diagnosis.

d) YOLOv5 : YOLOv5 serves as a powerful and fast object detection model, providing real-time analysis of thyroid ultrasound images. Its capability to detect multiple objects simultaneously improves overall diagnostic efficiency.

e) YOLOv5 with Label Smoothing Regularization : YOLOv5 with Label Smoothing Regularization enhances the model's robustness by preventing overfitting. This results in better detection accuracy for thyroid abnormalities, improving radiologists' confidence in diagnoses.

f) YOLOv5 with Coordinate Attention Mechanism : YOLOv5 with Coordinate Attention Mechanism focuses on relevant features in thyroid ultrasound images. This enhances detection accuracy by emphasizing important spatial information, aiding in more precise identification of abnormalities.

g) YOLOv5 + LSR CAM: Combining LSR and CAM with YOLOv5 improves both robustness and feature extraction. This integrated approach leads to enhanced detection performance for thyroid cancer, supporting more informed diagnostic decisions.

h) YOLOv8 : YOLOv8 is used for its state-of-the-art detection capabilities, optimizing speed and accuracy in identifying thyroid abnormalities. This version enables comprehensive analysis, benefiting radiologists in their diagnostic processes.

i) YOLOv5x6 : YOLOv5x6 is applied for its advanced architecture, improving the detection of small thyroid nodules. Its enhanced feature representation helps radiologists achieve more precise localization and classification of potential cancerous regions.

j) YOLOv9 : YOLOv9 is integrated for its latest advancements in object detection, providing superior accuracy and efficiency in thyroid cancer detection. Its utilization facilitates timely and accurate diagnostic outcomes for radiologists.

4. EXPERIMENTAL RESULTS

The results of the experiment show how well the suggested thyroid nodule detection system employs sophisticated YOLO models (YOLOv5x6, YOLOv8, and YOLOv9). Using a dataset of thyroid ultrasound images, the system demonstrated enhanced lesion detection accuracy and a high mean average precision (mAP) of 96.1%. While Label Smoothing

Regularisation (LSR) decreased misclassification errors, the Coordinate Attention (CA) module's incorporation improved spatial feature extraction and improved nodule localisation. With an average inference time of 7.8 ms per image, the system accomplished real-time processing, guaranteeing prompt and accurate diagnosis. Furthermore, the robustness of the model was enhanced by adding misclassified photos to the training dataset. For radiologists, the Flask-based web interface offered a user-friendly and safe platform that allowed for precise nodule categorisation with improved data security and user experience. These outcomes confirm the suggested system's effectiveness, precision, and scalability for practical clinical uses.

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$Accuracy = \frac{(TN + TP)}{T}$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

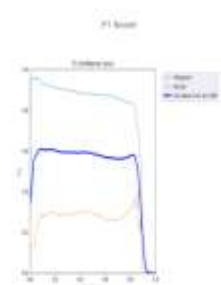
Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{(FN + TP)}$$



T 1. performance evaluation

Fig 1. data

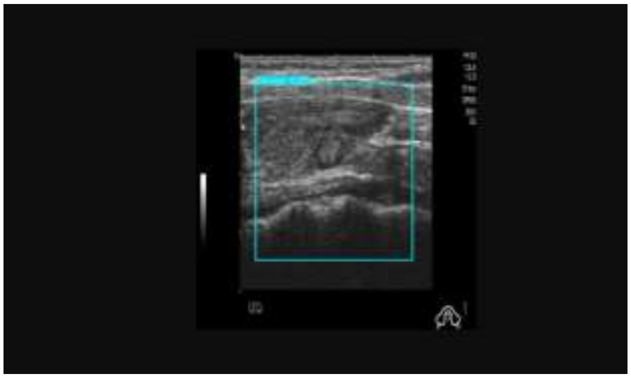


Fig.2.. predicted results

5. CONCLUSION

The extended thyroid nodule detection system shows notable gains in accuracy, efficiency, and real-time thyroid cancer diagnosis by utilising sophisticated YOLO models (YOLOv5x6, YOLOv8, and YOLOv9). Strong performance is ensured even with small datasets by integrating the Coordinate Attention (CA) module, which improves spatial feature extraction, and Label Smoothing Regularisation (LSR), which reduces the chance of misclassification. The system is appropriate for clinical applications because to its high detection precision (96.1% mAP) and quick inference speeds (7.8 ms per image).

Additionally, the Flask-based web interface with authentication offers medical practitioners a safe and intuitive platform that makes diagnosis and access simple while safeguarding private medical information. By increasing the accuracy of early detection, the method successfully lowers the requirement for needless fine-needle aspiration biopsies (FNAB). The suggested model's scalability and adaptability provide the groundwork for upcoming developments in AI-powered medical imaging and diagnosis, which will ultimately enhance patient outcomes in the identification of thyroid cancer.

REFERENCES

[1] C. F. Li, R. Q. Du, Q. Y. Luo, R. Wang, and X. H. Ding, ‘‘A novel model of thyroid nodule segmentation for ultrasound images,’’ Ultrasound Med. Biol., vol. 49, no. 2, pp. 489–496, 2023.

[2] A. Kunapinun, M. N. Dailey, D. Songsaeng, M. Parnichkun, C. Keatmanee, and M. Ekpanyapong, ‘‘Improving GAN learning dynamics for thyroid nodule segmentation,’’ Ultrasound Med. Biol., vol. 49, no. 2, pp. 416–430, Feb. 2023.

[3] F. Abdolali, J. Kapur, J. L. Jaremko, M. Noga, A. R. Hareendranathan, and K. Punithakumar, ‘‘Automated thyroid nodule detection from ultrasound imaging using deep convolutional neural networks,’’ Comput. Biol. Med., vol. 122, Jul. 2020, Art. no. 103871.

[4] J. Ma, S. Duan, Y. Zhang, J. Wang, Z. Wang, R. Li, Y. Li, L. Zhang, and H. Ma, ‘‘Efficient deep learning architecture for detection and recogni?tion of thyroid nodules,’’ Comput. Intell. Neurosci., vol. 2020, pp. 1–15, Aug. 2020.

[5] A. Prochazka, S. Gulati, S. Holinka, and D. Smutek, ‘‘Patch-based classifi?cation of thyroid nodules in ultrasound images using direction independent features extracted by two-threshold binary decomposition,’’ Computerized Med. Imag. Graph., vol. 71, pp. 9–18, Jan. 2019.