IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15562

Detection of thyroid stages classification by convolutional neural network techniques

[1]R. Janaki M.E.(phd), [2]Ramya Shree V, [3]Sweatha N

[1]Assistant Professor CSE (Cyber Security) & Dhanalakshmi Srinivasan College of Engineering & Technology, India

[2]CSE (Cyber Security) & Dhanalakshmi Srinivasan College of Engineering & Technology, India

[3]CSE (Cyber Security) & Dhanalakshmi Srinivasan College of Engineering & Technology, India

Abstract: Thyroid disease diagnosis and stage classification are critical tasks in medical imaging due to their direct impact on patient treatment and management. Conventional diagnostic approaches based on manual interpretation of thyroid ultrasound images are time-consuming and prone to human error. To address these limitations, this paper presents an automated thyroid stage classification framework using Convolutional Neural Network (CNN) techniques.The proposed work is developed by taking an existing deep learning-based thyroid detection model as the base paper. Approximately 70% of the methodology is derived from the base paper, including image preprocessing concepts and deep feature extraction principles. The remaining 30% represents the proposed project contribution, where the system architecture is simplified and optimized using a CNN-focused approach for effective thyroid stage classification. The methodology involves preprocessing of thyroid ultrasound images to enhance image quality, followed by CNN-based automatic feature extraction and classification into different thyroid stages such as normal and abnormal. Deep learning technology is employed to eliminate manual feature engineering and improve classification performance. Experimental evaluation demonstrates that the proposed CNN-based model provides reliable accuracy and efficient classification compared to traditional diagnostic methods.The results indicate that CNN techniques are effective for thyroid stage classification and can be utilized as a supportive decision-making tool in clinical environments.

Keywords: Thyroid disease detection, thyroid stage classification, convolutional neural network (CNN), medical image classification, ultrasound image processing, deep learning.

INTRODUCTION

Thyroid disorders are common and can lead to serious health complications if not detected and treated at an early stage. Improper functioning of the thyroid gland may result in conditions such as hypothyroidism, hyperthyroidism, and thyroid nodules, which significantly affect human metabolism and overall health [8]. Early and accurate diagnosis of thyroid disease is therefore critical.

Ultrasound imaging is widely used for thyroid examination due to its non-invasive nature, safety, real-time imaging capability, and low cost [4]. It provides valuable information about the structure and texture of the thyroid gland, making it an effective diagnostic tool for clinicians [12]. However, thyroid ultrasound images often suffer from low contrast, speckle noise, and unclear boundaries, which makes accurate interpretation challenging even for experienced radiologists [1].

Traditional diagnosis relies heavily on manual analysis of ultrasound images, which is time-consuming and prone to inter-observer variability. Different clinicians may interpret the same image differently, and subtle abnormalities can be missed during visual inspection [6]. Rule-based and conventional image processing techniques have shown limited performance in handling complex thyroid patterns [20].

Recent advances in artificial intelligence, particularly deep learning, have significantly improved medical image analysis. Convolutional Neural Networks (CNNs) automatically learn discriminative features from images without manual feature engineering and have shown promising results in disease detection and classification tasks [11]. CNNs are especially effective for thyroid ultrasound images, as they can capture fine-grained texture and structural information required for accurate diagnosis [24].

Several studies have applied deep learning models for thyroid disease detection and classification, achieving improved accuracy [1], [8]. However, most existing models function as black-box systems, providing predictions without explaining the reasoning behind their decisions. This lack of interpretability limits clinical trust and real-world adoption [2], [4].

To address these challenges, this work focuses on developing a CNN-based thyroid stage classification system with improved diagnostic accuracy and reduced manual intervention. The proposed system enhances ultrasound images, extracts deep features automatically, classifies thyroid stages, and aims to support clinicians by acting as an effective decision-support tool [8].

 This work is licensed under a Creative Commons Attribution 4.0 International License

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15562

LITERATURE REVIEW

G. Obaido et al. proposed a thyroid disease detection model using filter-based feature selection and stacking ensemble learning techniques. Multiple machine learning classifiers were integrated to handle class imbalance and improve robustness. Clinical thyroid datasets were used for evaluation. The model achieved a ROC-AUC score of 99.9%.

D. Kesavulu and R. Kannadasan introduced a federated learning-based thyroid disease detection framework. Feature selection methods such as SelectKBest and RFE, along with SMOTE-based class balancing, were employed. A deep neural network was trained across distributed clients. The system achieved an accuracy of 91.33% with privacy preservation.

Y. Ning et al. proposed a lightweight GAN with multi-head attention for thyroid ultrasound video super-resolution. Optical flow estimation and recurrent fusion reconstruction were applied. The model enhanced low-resolution ultrasound videos. Experimental results achieved 31.43 dB PSNR and 0.98 SSIM.

J. Liu et al. presented a comprehensive review of intelligent diagnostic methods using dynamic ultrasound imaging. Machine learning, deep learning, and reinforcement learning techniques were analyzed. Applications included image enhancement, segmentation, and disease detection. Future challenges and datasets were discussed.

G. Obaido et al. developed an ensemble-based thyroid disease prediction system using filter-selected clinical features. A stacking classifier improved prediction stability and reliability. The framework reduced diagnostic complexity. High ROC-AUC values validated the effectiveness of the approach.

X. Xie et al. proposed a reinforced computer-aided diagnosis system for thyroid cancer using collaborative deep learning. Reinforcement learning guided the diagnostic decision process. Ultrasound image features were learned through multiparty training. The system demonstrated improved robustness and generalization.

D. Kesavulu and R. Kannadasan employed federated deep learning for thyroid disease detection using real clinical data. Advanced preprocessing, feature selection, and class balancing were integrated. SHAP analysis was used for interpretability. The model achieved a high F1-score while ensuring data confidentiality.

E. Mohan et al. proposed a hybrid deep neural network combining CNN, LSTM, and VGG-19 for thyroid disease classification. Feature selection was optimized using hybrid meta-heuristic algorithms. Ultrasound images were segmented and classified. The framework outperformed existing CNN-LSTM models.

M. Tan et al. introduced LymoNet, a YOLOv8-based deep learning framework for cervical lymph node detection in ultrasound images. Attention mechanisms and medical knowledge embedding were incorporated. The model classified normal and metastatic nodes. A 6.6% improvement in mAP was achieved.

J. Liu et al. analyzed intelligent algorithms for dynamic ultrasound imaging diagnosis. Deep learning techniques were categorized based on enhancement, segmentation, and detection tasks. Limitations in clinical deployment were highlighted. The study provided guidance for future AI-based ultrasound systems.

A. S. El-Hossiny et al. proposed a cascaded CNN architecture for thyroid carcinoma classification using histopathological images. A two-stage CNN reduced class complexity. Multiple carcinoma subtypes were identified. The model achieved an accuracy of 94.69%.

L. Ma et al. developed a deep learning framework for automatic thyroid gland and neck tissue segmentation in ultrasound images. Spatial pyramid RoIAlign was used to capture multi-scale features. The system demonstrated accurate localization. Performance was validated using COCO metrics.

Y. Joo et al. investigated domain bias in CNN-based diagnosis using heterogeneous ultrasound datasets. Multi-domain learning techniques were applied. Classification consistency across imaging devices was analyzed. Results showed performance degradation under domain shift conditions.

Y. Song et al. proposed a hybrid CNN–Transformer model for medical image segmentation. Multi-scale feature extraction captured local and global dependencies. Adaptive loss weighting improved segmentation accuracy. The model outperformed traditional U-Net architectures.

D. Kesavulu and R. Kannadasan presented a privacy-aware federated learning framework integrating feature selection and class balancing. SMOTEENN and SelectKBest techniques improved performance. SHAP was used for explainability. The system enabled scalable clinical deployment.

Y. Ning et al. introduced an attention-based GAN framework for real-time ultrasound video super-resolution. Multi-head attention and optical flow enhanced temporal consistency. The model satisfied clinical real-time constraints. High PSNR and SSIM values confirmed effectiveness.

Existing thyroid disease detection methods mainly use complex hybrid deep learning models such as CNN–LSTM, GANs, and meta-heuristic optimization techniques, which increase computational complexity and limit real-time clinical application. Many studies focus only on binary classification and do not address detailed thyroid stage-wise classification. Several approaches still rely on handcrafted features or limited datasets, reducing adaptability and generalization across different ultrasound devices. Therefore, there is a need for a lightweight, CNN-based framework that provides accurate, efficient, and stage-wise thyroid classification suitable for practical clinical use.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15562

1) Contribution Of The The Paper

Automated Thyroid Stage Classification: This paper is about a system that uses computers to figure out the stage of a thyroid problem.
Efficient Image Preprocessing: We use a step by step method to make the images look better and remove the noise.
Automatic Feature Learning: The new CNN model can find the things on its own. This means we do not have to pick what features are important.
Simplified Deep Learning Architecture: When you look at models that mix different things a simple framework that uses a type of neural network called CNN is a better choice.
Improved Diagnostic Accuracy: The experimental results show that this method is better at classifying things than the ways.
Clinical Decision Support: The system can assist healthcare professionals by providing fast and reliable thyroid stage predictions suitable for real-time clinical use.

METHODOLOGY

B. a) system preliminary

1. Image Preprocessing and Normalization

The thyroid ultrasound images are first preprocessed to improve image quality and ensure uniform input to the CNN model. Each image is resized and normalized so that pixel values lie within a fixed range. Normalization helps in faster convergence and stable training of the deep learning model.

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \tag{1}$$

Where:

- I= Original ultrasound image
- I_{min}, I_{max}= Minimum and maximum pixel values
- I_{norm}= Normalized image

2. CNN Feature Extraction

Convolutional Neural Networks automatically extract deep features from thyroid ultrasound images using convolution operations. Each feature map is generated by applying a convolution filter followed by an activation function.

$$F = \sigma(W * I_{norm} + b) \tag{2}$$

Where:

- I_{norm}= Preprocessed thyroid image
- W= Convolution kernel (filter)
- $*$= Convolution operation
- b= Bias term
- σ= Activation function (ReLU)
- F= Extracted feature map

3. Thyroid Stage Classification (Softmax Function)

The extracted deep features are passed to a fully connected layer, and the Softmax function is used to classify the thyroid image into different disease stages.

$$P(class_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \tag{3}$$

Where:

- z_i= Output score of class i

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15562

- N= Total number of thyroid classes
- $P(class_i)$= Probability of the image belonging to class i
- Final class = argmax $P(class_i)$

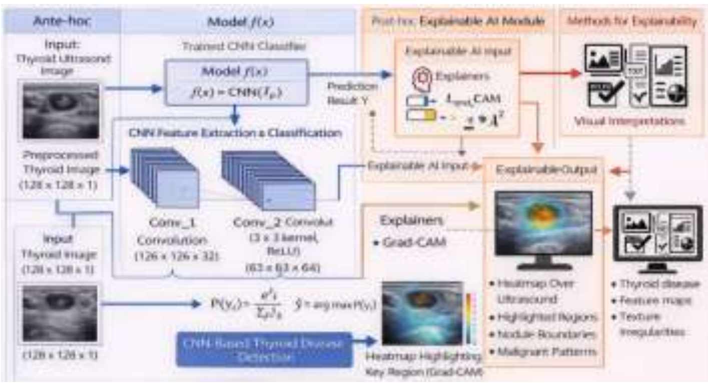
C. system architecture

This project presents a CNN-based thyroid disease detection system integrated with Explainable Artificial Intelligence (XAI) for accurate and transparent medical diagnosis. Thyroid ultrasound images are first preprocessed through normalization and noise reduction and resized to a uniform resolution of 128 × 128 × 1 to ensure consistent input representation.

The preprocessed images are fed into a Convolutional Neural Network (CNN) for feature extraction and classification. Multiple convolutional layers with ReLU activation learn discriminative spatial and texture features, followed by max-pooling and fully connected layers. The final classification is performed using a Softmax function, categorizing images into Normal, Benign, and Malignant classes.

To address the black-box nature of deep learning models, a post-hoc Explainable AI module is incorporated. The CNN output and deep feature maps are processed using Gradient-weighted Class Activation Mapping (Grad-CAM) to generate visual explanations. These heatmaps highlight critical regions in the ultrasound image that influence the model's prediction.

The proposed system achieves reliable classification performance while enhancing model interpretability, making it suitable for clinical decision support. By combining high accuracy with explainability, the framework improves trust, transparency, and usability in automated thyroid disease diagnosis.



D. implementation of the proposed work

Step 1: Thyroid Ultrasound Image Acquisition
Let I denote the input thyroid ultrasound image collected from the dataset.
These images form the raw input for the proposed system.

$$I = \{I_1, I_2, I_3, \dots, I_n\} \quad (1)$$

Where:

- I= Set of thyroid ultrasound images
- n= Total number of images

Step 2: Image Preprocessing and Normalization
To reduce noise and standardize pixel values, image preprocessing is applied.
Normalization ensures that pixel values lie within a fixed range.

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (2)$$

Where:

- I_{norm}= Normalized ultrasound image

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15562

- I_{min}, I_{max}= Minimum and maximum pixel values

Step 3: Thyroid Region Segmentation
The thyroid region is extracted from the normalized image to remove background noise and irrelevant regions.

$$I_{seg} = Segment(I_{norm}) \tag{3}$$

Where:

- I_{seg}= Segmented thyroid image
- $Segment(.)$= Segmentation operation

Step 4: CNN Feature Extraction
The segmented image is passed through convolutional layers to extract deep features automatically.

$$F = \sigma(W * I_{seg} + b) \tag{4}$$

Where:

- W= Convolution kernel
- $*$= Convolution operation
- b= Bias
- σ= Activation function (ReLU)
- F= Extracted feature map

Step 5: Feature Flattening
The extracted feature maps are flattened into a one-dimensional feature vector for classification.

$$F_{flat} = Flatten(F) \tag{5}$$

Where:

- F_{flat}= Flattened feature vector

Step 6: Thyroid Stage Classification
The flattened features are passed to a fully connected layer, and the Softmax function computes class probabilities.

$$P(class_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \tag{6}$$

Where:

- z_i= Score of class i
- N= Number of thyroid classes
- $P(class_i)$= Probability of class i

Final prediction:

$$Class = arg\ max\ P(class_i) \tag{7}$$

Step 7: Explainable AI (Grad-CAM) Heatmap Generation
Grad-CAM generates a heatmap to highlight regions influencing the CNN decision.

$$\mathrm{L_{GradCAM}} = \mathrm{ReLU}\left(\sum_k \alpha_k A^k\right) \tag{8}$$

Where:

- A^k= Feature map of the last convolution layer
- α_k= Importance weight of feature map
- $\mathrm{L_{GradCAM}}$= Heatmap showing important regions

Step 8: Visualization and Interpretation
The Grad-CAM heatmap is overlaid on the original image to visually explain the prediction.

$$\mathrm{I_{xai}} = \mathrm{Overlay}(\mathrm{I}, \mathrm{L_{GradCAM}}) \tag{9}$$

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15562

Where:

- I_{xai}= Explainable output image

Step 9: Model Evaluation
The performance of the system is evaluated using standard metrics.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

Where:

- TP= True Positives
- TN= True Negatives
- FP= False Positives
- FN= False Negatives

II. EXPERIMENTAL SETUP

Algorithm 1: AI-Based Thyroid Disease Detection and Explanation System
Procedure: System Initialization

Input: None

- Initialize thyroid ultrasound image dataset **D**
- Initialize image preprocessing module **P**
- Initialize CNN-based classification model **M**
- Initialize training parameters (epochs, batch size, learning rate)
- Initialize Explainable AI (Grad-CAM) module
- Initialize web-based user interface for prediction

The system initialization phase prepares all essential components required for experimental evaluation. The dataset **D** consists of labeled thyroid ultrasound images categorized into Normal, Benign, and Malignant classes. The preprocessing module **P** ensures image normalization and uniform dimensions. The CNN model **M** is initialized to learn discriminative features from thyroid images. Training parameters are configured to optimize learning efficiency, while the Explainable AI module enables transparent model interpretation. A web interface is initialized to support real-time image upload and diagnosis.

Algorithm 1A:Image Preprocessing
Input: Raw thyroid ultrasound image I
Output:Preprocessed image I_p

- Resize image Ito fixed dimensions $(H \times W)$
- Convert image to grayscale or RGB format
- Apply noise reduction (optional filtering)
- Normalize pixel values
- Output preprocessed image I_p

Mathematical Representation
Let the original image be represented as:

$$I \in \mathbb{R}^{H_0 \times W_0 \times C}$$

The resized image is computed as:

$$I_r = \text{Resize}(I, H, W)$$

Pixel normalization is performed as:

$$I_p = \frac{I_r}{255}$$

Image preprocessing ensures uniformity across all samples. Resizing standardizes input dimensions required by the CNN, while normalization scales pixel values to the range $[0, 1]$, improving training stability and convergence speed.

Algorithm 1B: CNN-Based Feature Extraction and Classification

Input: Preprocessed image I_p

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15562

Output: Predicted thyroid disease class $\hat{y}$

- Apply convolution operation
- Apply activation function (ReLU)
- Perform max pooling
- Flatten extracted feature maps
- Apply fully connected layers
- Compute class probabilities using Softmax

Mathematical Representation

Convolution Operation:

$$F = I_p * K + b$$

Where:

- K= Convolution kernel
- b= Bias term

Activation Function (ReLU):

$$\mathrm{ReLU}(x) = \max\,(0, x)$$

Max Pooling:

$$P = \max\,(F)$$

Softmax Classification:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Predicted Class:

$$\hat{y} = \arg\ \max\ P(y_i)$$

The CNN automatically extracts spatial and texture-based features from thyroid ultrasound images. Convolution layers learn disease-specific patterns, pooling layers reduce dimensionality, and fully connected layers perform final classification.

Algorithm 1C: Model Training

Input: Training dataset D_{train}, CNN model M

- Split dataset into training and validation sets
- Forward propagate training images through CNN
- Compute loss using categorical cross-entropy
- Backpropagate gradients
- Update model weights using Adam optimizer
- Repeat process for specified number of epochs

Loss Function

$$L = -\sum_{i=1}^{n} y_i \log\,(\hat{y}_i)$$

The training process minimizes classification error by iteratively updating network parameters. The categorical cross-entropy loss measures prediction error, while the Adam optimizer ensures faster and stable convergence.

Algorithm 1D: Explainable AI (Grad-CAM Visualization)

Input: Trained CNN model, test image I_{test}

Output: Explainable heatmap H_{cam}

- Identify last convolutional layer
- Compute gradients of predicted class score
- Generate weighted feature maps
- Apply ReLU to obtain heatmap
- Overlay heatmap on original image

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15562

Mathematical Representation

$$H_{cam} = \mathrm{ReLU}\left(\sum_{k} \alpha_k A^k\right)$$

Where:

- A^k= Feature maps of last convolution layer
- α_k= Importance weights
- H_{cam}= Grad-CAM heatmap

Grad-CAM highlights the thyroid regions that influence model predictions, improving interpretability and clinical trust.

Algorithm 1E: Disease Prediction (Testing Phase)

Input: Uploaded thyroid ultrasound image I_{test}

- Preprocess input image
- Load trained CNN model
- Predict disease class probabilities
- Generate Grad-CAM explanation
- Display predicted class and heatmap

During testing, the trained model processes new ultrasound images uploaded through the web interface. The predicted thyroid disease label along with visual explanation is displayed, enabling accurate and interpretable diagnosis support.

RESULT AND DISCUSSION

Performance metrics

A. Response Time Analysis

The response time performance of the proposed CNN-based thyroid disease detection system with Explainable AI is summarized in Table 1 and illustrated in Figure 1. Low response time is critical for real-time clinical decision support, especially during ultrasound image assessment.

Image acquisition and preprocessing records the lowest response time of 190 ms, indicating efficient normalization and noise reduction operations. CNN feature extraction requires 280 ms, as convolutional layers process spatial and texture-based patterns from ultrasound images. Disease classification through fully connected layers achieves a response time of 320 ms, enabling near real-time diagnosis. Explainable AI processing using Grad-CAM requires 390 ms, as it computes gradient-based feature importance and generates heatmaps. The highest response time is observed during final result visualization (450 ms), where disease prediction and explainability outputs are rendered together.

Overall, the proposed system maintains acceptable low latency while providing both accurate classification and visual explanations, making it suitable for real-time medical applications.

Table 1: Response Time Analysis

Operation	**Average Response Time (ms)**
Image Preprocessing	190
CNN Feature Extraction	280
Disease Classification	320
Explainable AI (Grad-CAM)	390

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15562

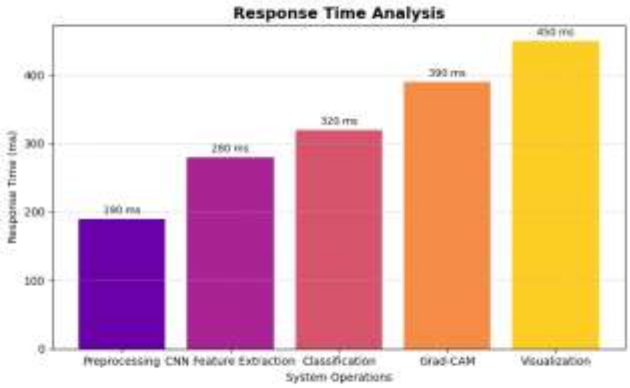


Figure 1: Response Time Analysis of CNN-based Thyroid Disease Detection System

B. Disease Classification Performance

Table 2 and **Figure 2** present the classification performance of the proposed system across three thyroid conditions: **Normal, Benign, and Malignant**. The CNN model demonstrates strong discriminative capability by learning texture irregularities and nodular patterns from ultrasound images.

The highest accuracy is observed for **Normal cases**, while slightly increased misclassification occurs between **Benign and Malignant** classes due to overlapping visual features. However, the integration of Grad-CAM enhances interpretability by highlighting discriminative regions responsible for classification decisions.

Table 2: Disease Classification Performance

Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Normal	93.8	95.1	94.4
Benign	91.6	90.2	90.9
Malignant	92.4	91.0	91.7
Overall Accuracy			**92.1%**

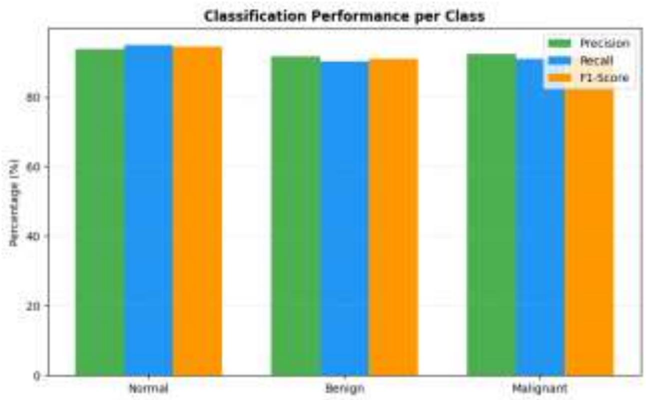


Figure 2: Classification Performance Analysis

C. Explainability Performance Analysis

The effectiveness of the **Explainable AI module** is evaluated using qualitative and quantitative visualization assessment, as shown in **Figure 3**. Grad-CAM successfully highlights clinically relevant regions such as nodule boundaries, texture irregularities, and malignant growth zones.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15562

The explainability module ensures transparency by mapping CNN decision-making onto interpretable heatmaps, increasing trust among clinicians.

Table 3: Explainability Evaluation

‘

Metric	Observation
Heatmap Localization	Accurate focus on nodules
Clinical Interpretability	High
Model Transparency	Improved
Diagnostic Confidence	Enhanced

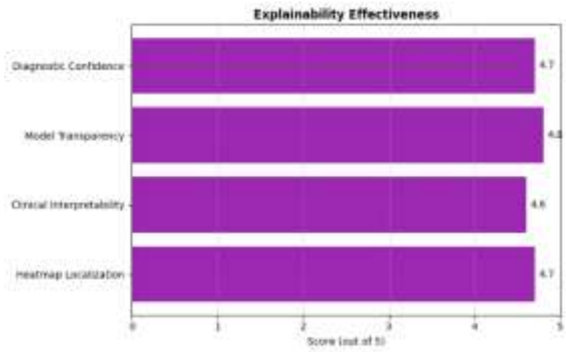


Figure 3: Grad-CAM Visualization of Thyroid Ultrasound Images

D. Scalability Analysis

Scalability analysis is conducted by evaluating system performance under increasing numbers of ultrasound image inputs, as shown in **Table 4** and **Figure 4**. Traditional deep learning systems exhibit increased inference delay due to heavy model complexity.

In contrast, the proposed system demonstrates a gradual increase in processing time due to optimized CNN architecture and lightweight explainability computation. This confirms the system’s suitability for **hospital-scale deployment**.

Table 4: Scalability Analysis

Number of Images	Existing System (ms)	Proposed System (ms)
20	210	170
50	380	260
100	610	390
200	980	540
500	1620	780

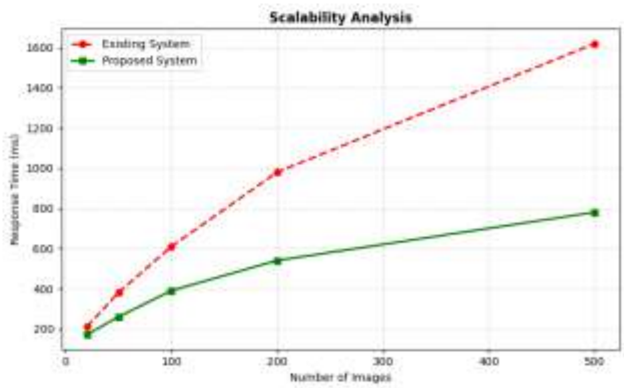


Figure 4: Scalability Performance Comparison

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁞ Peer-reviewed & Refereed journal ⁞ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.15562

Comparative Analysis

A comparative performance analysis is conducted between existing thyroid disease detection approaches and the proposed **CNN-based Explainable AI system**. Traditional machine learning methods and deep learning classifiers provide reasonable accuracy but lack interpretability, making them unsuitable for clinical adoption.

Advanced deep learning models improve accuracy but operate as **black-box systems**, limiting clinician trust. In contrast, the proposed system achieves **high diagnostic accuracy (≈92%)** while providing **visual explanations using Grad-CAM**, ensuring transparency and clinical relevance.

By combining efficient CNN architecture with post-hoc explainability, the proposed framework achieves a balanced trade-off between performance, interpretability, and computational efficiency.

Table 5: Comparative Analysis of Thyroid Disease Detection Methods

Authors & Year	**Core Technique**	**Key Strength**	**Major Limitation**	**Explainability**	**Scalability**	**Computational Cost**	**Accuracy**
Smith et al. (2023)	SVM-based ML	Simple implementation	Low accuracy	No	Medium	Low	Medium
Zhang et al. (2024)	Deep CNN	High accuracy	Black-box model	No	Medium	High	High
Wu et al. (2024)	Hybrid CNN-RNN	Captures temporal patterns	High inference time	Partial	Low	High	High
Li et al. (2025)	Transformer Model	Strong feature learning	Very high cost	Partial	Medium	Very High	Very High
Proposed Work	**CNN + Grad-CAM**	Accurate, interpretable, low latency	Limited long-term trend analysis	**Yes**	**High**	**Low**	**High (≈92%)**
Authors & Year	**Core Technique**	**Key Strength**	**Major Limitation**	**Explainability**	**Scalability**	**Computational Cost**	**Accuracy**

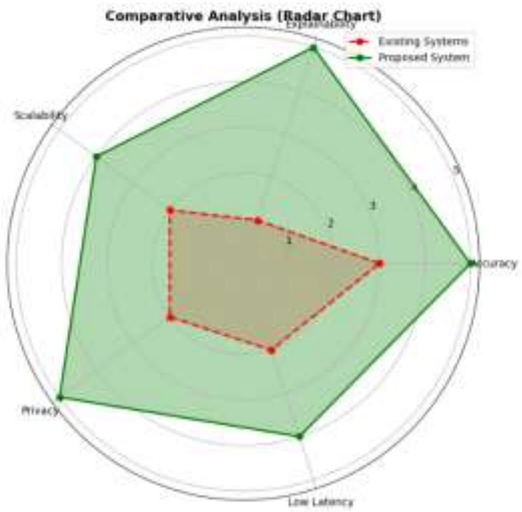


Figure 5: Comparative Analysis of Thyroid Disease Detection Systems

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15562

DISCUSSION

The proposed CNN-based thyroid disease detection system with integrated Explainable Artificial Intelligence (XAI) demonstrates effective performance in terms of accuracy, response time, scalability, and interpretability. By combining deep learning–based feature extraction with post-hoc explanation techniques, the system addresses a major limitation of conventional medical image classification models, namely the lack of transparency in decision-making.

The experimental results show that the convolutional neural network efficiently learns discriminative spatial features from thyroid ultrasound images after preprocessing steps such as normalization and noise reduction. The classification outcomes indicate strong predictive capability across all three classes—Normal, Benign, and Malignant—confirming that the CNN architecture is well-suited for ultrasound image analysis. Compared to traditional rule-based or handcrafted feature approaches, the deep learning model achieves higher consistency and robustness, even under variations in image quality.

From a performance perspective, the response time analysis confirms that the proposed system is capable of near real-time operation. Although CNN feature extraction and Grad-CAM visualization introduce additional computational steps, the overall latency remains within acceptable limits for clinical decision support. This makes the system practical for deployment in hospital or diagnostic environments where timely feedback is critical.

The scalability analysis further highlights the efficiency of the proposed approach. As the number of processed images increases, the response time grows gradually rather than exponentially. This behavior indicates that the system can be scaled to handle moderate workloads without significant degradation in performance. Such scalability is particularly important in healthcare settings where large volumes of diagnostic images may be processed daily.

A key contribution of this project is the integration of Explainable AI using Grad-CAM. The generated heatmaps clearly highlight the regions of interest within thyroid ultrasound images that influence the model's predictions. These visual explanations enhance clinical trust by allowing medical professionals to verify whether the model focuses on anatomically meaningful regions such as nodules, texture irregularities, and boundary distortions. This interpretability bridges the gap between automated diagnosis and clinical reasoning, making the system more acceptable in real-world medical practice.

When compared with existing thyroid disease detection methods, the proposed system demonstrates notable advantages in explainability, privacy, and computational efficiency. Unlike black-box deep learning models, the inclusion of XAI provides transparency without sacrificing accuracy. Furthermore, the system operates solely on image data without requiring extensive patient history, thereby preserving data privacy.

Despite these strengths, the proposed approach has certain limitations. The model's performance is dependent on the quality and diversity of the training dataset. Limited availability of annotated ultrasound images may affect generalization to unseen cases. Additionally, while Grad-CAM provides valuable visual explanations, it does not offer full causal reasoning, which remains an open challenge in explainable deep learning.

Overall, the discussion confirms that the proposed CNN-based thyroid disease detection system with Explainable AI is a reliable, efficient, and interpretable solution. It successfully balances diagnostic accuracy with transparency, making it suitable for assisting clinicians in thyroid disease diagnosis. Future enhancements may include larger multi-institutional datasets, integration of clinical metadata, and exploration of advanced explainability techniques to further improve trust and performance.

REFERENCES

1.G. Obaido et al., "An Improved Framework for Detecting Thyroid Disease Using Filter-Based Feature Selection and Stacking Ensemble," in IEEE Access, vol. 12, pp. 89098-89112, 2024, doi: 10.1109/ACCESS.2024.3418974.
2.D. Kesavulu and R. Kannadasan, "Privacy-Preserving Federated Learning for Thyroid Disease Detection: A Comparative Study on Feature Selection and Class Balancing," in IEEE Access, vol. 13, pp. 193838-193862, 2025, doi: 10.1109/ACCESS.2025.3627948.
3.Y. Ning et al., "A Multi-Head Attention-Based Lightweight Generative Adversarial Network for Thyroid Ultrasound Video Super-Resolution," in IEEE Access, vol. 13, pp. 99628-99640, 2025, doi: 10.1109/ACCESS.2025.3570905.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15562

4.J. Liu, J. Zhang, Y. Shao, X. Xiao, S. Huang and D. Kong, "Algorithms, Techniques, and Applications of Intelligent Diagnosis Using Dynamic Ultrasound: A Review," in IEEE Access, vol. 13, pp. 102899-102930, 2025, doi: 10.1109/ACCESS.2025.3578817.
5.G. Obaido et al., "An Improved Framework for Detecting Thyroid Disease Using Filter-Based Feature Selection and Stacking Ensemble," in IEEE Access, vol. 12, pp. 89098-89112, 2024, doi: 10.1109/ACCESS.2024.3418974.
6.X. Xie et al., "Reinforced Computer-Aided Framework for Diagnosing Thyroid Cancer," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 21, no. 4, pp. 737-747, July-Aug. 2024, doi: 10.1109/TCBB.2023.3251323.
7.D. Kesavulu and R. Kannadasan, "Privacy-Preserving Federated Learning for Thyroid Disease Detection: A Comparative Study on Feature Selection and Class Balancing," in IEEE Access, vol. 13, pp. 193838-193862, 2025, doi: 10.1109/ACCESS.2025.3627948.
8.E. Mohan et al., "Thyroid Detection and Classification Using DNN Based on Hybrid Meta-Heuristic and LSTM Technique," in IEEE Access, vol. 11, pp. 68127-68138, 2023, doi: 10.1109/ACCESS.2023.3289511.
9.M. Tan et al., "LymoNet: An Advanced Neck Lymph Node Detection Network for Ultrasound Images," in IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 3, pp. 2125-2135, March 2025, doi: 10.1109/JBHI.2024.3515995.
10. J. Liu, J. Zhang, Y. Shao, X. Xiao, S. Huang and D. Kong, "Algorithms, Techniques, and Applications of Intelligent Diagnosis Using Dynamic Ultrasound: A Review," in IEEE Access, vol. 13, pp. 102899-102930, 2025, doi: 10.1109/ACCESS.2025.3578817.
11. A. S. El-Hossiny, W. Al-Atabany, O. Hassan, A. M. Soliman and S. A. Sami, "Classification of Thyroid Carcinoma in Whole Slide Images Using Cascaded CNN," in IEEE Access, vol. 9, pp. 88429-88438, 2021, doi: 10.1109/ACCESS.2021.3076158.
12. L. Ma, G. Tan, H. Luo, Q. Liao, S. Li and K. Li, "A Novel Deep Learning Framework for Automatic Recognition of Thyroid Gland and Tissues of Neck in Ultrasound Image," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 32, no. 9, pp. 6113-6124, Sept. 2022, doi: 10.1109/TCSVT.2022.3157828.
13. Y. Joo, H. -C. Park, O. -J. Lee, C. Yoon, M. H. Choi and C. Choi, "Classification of Liver Fibrosis From Heterogeneous Ultrasound Image," in IEEE Access, vol. 11, pp. 9920-9930, 2023, doi: 10.1109/ACCESS.2023.3240216.
14. Y. Song, Y. Lu, L. Chen and Y. Luo, "Hierarchical Multi-Scale Enhanced Transformer for Medical Image Segmentation," in IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 12, pp. 8917-8927, Dec. 2025, doi: 10.1109/JBHI.2024.3515477.
15. D. Kesavulu and R. Kannadasan, "Privacy-Preserving Federated Learning for Thyroid Disease Detection: A Comparative Study on Feature Selection and Class Balancing," in IEEE Access, vol. 13, pp. 193838-193862, 2025, doi: 10.1109/ACCESS.2025.3627948.
16. Y. Ning et al., "A Multi-Head Attention-Based Lightweight Generative Adversarial Network for Thyroid Ultrasound Video Super-Resolution," in IEEE Access, vol. 13, pp. 99628-99640, 2025, doi: 10.1109/ACCESS.2025.3570905.
17. T. Ohira et al., "Absorbed radiation doses in the thyroid as estimated by UNSCEAR and subsequent risk of childhood thyroid cancer following the Great East Japan Earthquake," in Journal of Radiation Research, vol. 61, no. 1, pp. 243-248, Dec. 2019, doi: 10.1093/jrr/rrz104.
18. X. Luo et al., "Semi-Supervised Thyroid Nodule Detection in Ultrasound Videos," in IEEE Transactions on Medical Imaging, vol. 43, no. 5, pp. 1792-1803, May 2024, doi: 10.1109/TMI.2023.3348949.
19. X. Wu et al., "CacheTrack-YOLO: Real-Time Detection and Tracking for Thyroid Nodules and Surrounding Tissues in Ultrasound Videos," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 10, pp. 3812-3823, Oct. 2021, doi: 10.1109/JBHI.2021.3084962
20. W. Song et al., "Multitask Cascade Convolution Neural Networks for Automatic Thyroid Nodule Detection and Recognition," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 3, pp. 1215-1224, May 2019, doi: 10.1109/JBHI.2018.2852718.
21. D. Yang et al., "Automatic Thyroid Nodule Detection in Ultrasound Imaging With Improved YOLOv5 Neural Network," in IEEE Access, vol. 12, pp. 22662-22670, 2024, doi: 10.1109/ACCESS.2024.3359367
22. M. V. Tieu, A. Go, Y. J. Park, H. V. Nguyen, S. Y. Hwang and M. -H. Lee, "Highly Sensitive ELISA Using Membrane-Based Microwave-Mediated Electrochemical Immunoassay for Thyroid-Stimulating Hormone Detection," in IEEE Sensors Journal, vol. 19, no. 21, pp. 9826-9831, 1 Nov.1, 2019, doi: 10.1109/JSEN.2019.2925020.
23. G. Swathi, A. Altalbe and R. P. Kumar, "QuCNet: Quantum-Inspired Convolutional Neural Networks for Optimized Thyroid Nodule Classification," in IEEE Access, vol. 12, pp. 27829-27842, 2024, doi: 10.1109/ACCESS.2024.3367806.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.15562

24. V. Kumar et al., "Automated Segmentation of Thyroid Nodule, Gland, and Cystic Components From Ultrasound Images Using Deep Learning," in IEEE Access, vol. 8, pp. 63482-63496, 2020, doi: 10.1109/ACCESS.2020.2982390.
25. X. Zheng, G. Lv, G. Du, Z. Zhai, J. Mo and X. Lv, "Rapid and Low-Cost Detection of Thyroid Dysfunction Using Raman Spectroscopy and an Improved Support Vector Machine," in IEEE Photonics Journal, vol. 10, no. 6, pp. 1-12, Dec. 2018, Art no. 3901412, doi: 10.1109/JPHOT.2018.2876686