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Comparative Study of Deep Learning Methods for Thyroid Cancer Detection

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Abstract

Deep learning (DL) has emerged as a powerful tool for improving the accuracy and consistency of thyroid cancer detection from ultrasound images. While numerous DL-based models have been proposed, their clinical applicability, generalizability, and interpretability vary significantly. This paper presents a comparative review of five influential and peer-reviewed deep learning paradigms for thyroid cancer detection: Swin-Attention Segmentation, Weakly Supervised Segmentation, Vision Foundation Models, the diffusion-based Tiger Model, and the human-interpretable TiNet framework. These models represent diverse methodological directions, including attention-driven segmentation, annotation-efficient learning, foundation model adaptation, generative data augmentation, and explainable diagnostic reporting. The review critically analyzes their architectural design, dataset usage, performance metrics, interpretability, and deployment readiness. Key research gaps are identified, including limited multi-center generalization, insufficient handling of rare thyroid cancer subtypes, inconsistent clinical benchmarking, and challenges in real-world deployment. By emphasizing clinical relevance alongside technical performance, this review aims to guide future research toward developing robust, interpretable, and clinically integrable AI systems for thyroid cancer diagnosis.

Introduction

Thyroid nodules are among the most prevalent endocrine abnormalities, affecting a significant proportion of the global population. Although most nodules are benign, a small but clinically critical subset is malignant, necessitating accurate and timely diagnosis. Ultrasound imaging is the primary modality for thyroid nodule evaluation due to its non-invasive nature, affordability, and real-time imaging capability. However, ultrasound interpretation remains highly operator-dependent, often leading to inter-observer variability and inconsistent diagnostic outcomes.

Recent advances in artificial intelligence (AI), particularly deep learning (DL), have shown considerable promise in automating thyroid ultrasound analysis. Deep learning models have been applied to key diagnostic tasks such as nodule segmentation, benign–malignant classification, and structured report generation. Architectures ranging from convolutional neural networks (CNNs) to Transformer-based and multimodal frameworks have demonstrated performance comparable to, and in some cases exceeding, expert radiologists. Despite these advances, many proposed models suffer from limited generalizability, insufficient interpretability, dependence on large annotated datasets, and lack of alignment with clinical workflows.

Moreover, the rapid proliferation of DL-based thyroid imaging studies has resulted in fragmented literature, making it difficult for researchers and clinicians to assess which approaches are most suitable for real-world deployment. Performance comparisons are often inconsistent due to varying datasets, evaluation metrics, and experimental protocols. Consequently, there is a growing need for a structured and clinically oriented comparative analysis of state-of-the-art deep learning approaches in thyroid cancer detection. The key contributions of this paper are as follows:

- Comparative Analysis: A structured comparative review of five clinically influential deep learning paradigms for thyroid cancer detection using ultrasound imaging.
- Clinical Perspective: Evaluation of models beyond accuracy, emphasizing interpretability, deployment feasibility, real-time performance, and clinical usability.
- Gap Identification: Identification of persistent research gaps, including limited multi-center generalization, poor rare subtype recognition, and inconsistent clinical benchmarking.
- Translational Guidance: Practical insights and recommendations to bridge the gap between experimental AI models and deployable clinical decision support systems.

By integrating technical and clinical perspectives, this review provides a consolidated reference for researchers, clinicians, and developers working toward trustworthy AI-based thyroid diagnostic systems.

Literature Review

Deep learning methods for thyroid ultrasound analysis have evolved substantially in recent years, with segmentation emerging as a dominant task. Transformer-based architectures, particularly those incorporating attention mechanisms, have achieved impressive accuracy. Yang et al. [1] proposed a self-attention mechanism-based Swin U-Net model for improving the diagnostic accuracy of thyroid nodule segmentation in ultrasound images. By using Swin Transformer blocks within a U-Net structure, the model quite effectively captures contextual dependencies and improves feature representation. This strategy resolves segmentation problems crucial to precise clinical diagnosis, with a more stable tool for medical imaging workflows

Sun et al. [2] introduced CLIP-TNseg, a multi-modal hybrid framework which unites the semantic richness of a frozen CLIP model with the refinement of spatial detail of U-Net- style residual blocks. The two branches are coarse-grained and detailed—that collectively add to interpretability and generalization. The findings showed enhanced segmentation performance on several datasets, affirming its robustness and accuracy.

Dialameh et al. [3] introduced DualSwinUnet++, a dual decoder transformer architecture in particular applied to papillary thyroid microcarcinoma segmentation (PTMC). The model uses gland-level context and a residual information flow mechanism to address typical illustrates issues with small lesion size and acoustic shadowing. It obtains greater delineation accuracy, and hence is appropriate for challenging clinical cases of PTMC.

Wei et al. [4] put forward an ensemble deep learning model concentrated on enhancing the multicenter classification of thyroid nodule appearance from ultrasound images. Through integrating data from different clinical sources, the model increases generalizability and resiliency in different healthcare settings. This strategy allows for better discrimination between benign and malignant nodules, consistent with repeated diagnosis in different environments.

Ajilisa et al. [5] created a deep learning model that has a more advanced Inception Network and multilevel use transfer learning to establish thyroid nodules. The method effectively addresses the problem of small datasets by transmitting representations made at different levels, which results in improved classification performance. It demonstrates greater discrimination between malignant and benign nodules on ultrasound imaging.

Wang et al. [6] presented ThyroNet-X4 Genesis, a sophisticated model based on ResNet architecture with enhancements such as grouped convolutions and large kernels for better feature extraction. The model is good at both internal and external data sets for malignancy classification of thyroid nodules. Its concept is to minimize diagnostic errors and aid clinical decision-making in thyroid cancer screening.

Chi et al. [7] proposed a weakly supervised segmentation framework that enhances thyroid nodule delineation with high-rationality loss and high-confidence pseudo-labels operations. The approach combines geometric transformations with MedSAM outputs that generate stable labels and comprises alignment loss to cope with annotation constraints. It effectively segments nodules of different morphologies even when annotations are coarse or thin.

Tao et al. [8] introduced a deep learning model that includes multimodal ultrasound images for diagnosing suspicious thyroid nodules. By correlating the visual data of different ultrasound modalities, the method improves the model's capability to make accurate predictions to identify malignant lesions. This multimodal fusion is especially useful for complicated or ambiguous cases in clinical practice.

Kim et al. [9] investigated the clinical use of CNNbased models such as ResNet, DenseNet, and EfficientNet for multiview ultrasound thyroid nodule classification images. The research sets higher diagnostic performance while also pointing out real-world challenges implementation. It provides realtime insight into balancing technical efficiency with clinical applicability in AI-aided diagnosis.

Pham Ngoc et al. [10] introduced ThyroEffi 1.0, an cost effective high-performance design deep learning system multiclass classification of thyroid FNAB images. The model accurately classifies samples as Benign, Indeterminate/ Suspicious and Malignant categories, supporting better clinical decision making. It involves computational and data limitations with good diagnostic accuracy and reducing inter-observer variability.

Chi et al. [11] introduced a weakly supervised segmentation network using multi-level labels designed with four-point annotations to enhance nodule segmentation. This approach increases label richness and enable the network to better separating nodules from background manually with low input. By enhancing spatial limits, it actually alleviates underfitting and overfitting, enhancing segmentation precision on ultrasound examination.

Zhao et al. [12] proposed an asymmetric learning framework using simple clinical annotations like aspect ratios for automating thyroid nodule segmentation. The method produces pseudo-labels of conservative and radical tendencies and trains two specialized networks. An inconsistency-aware dynamic mixing module enhances further accuracy through correcting segmentation imbalances, lowering dependence on expert marked information.

Dong et al. [13] proposed DPAM-UNet++, an enhanced UNet++ model with a Dual-Path Attention Mechanism integrated into its skip connections for improved thyroid nodule segmentation. The modules of attention effectively capture global contextual information offering segmentation precision and efficiency. The model outperforms conventional approaches by being better than comparison metrics such as IoU and F1-score.

Zhang et al. [14] introduced a new flexible framework hierarchical vision base model, i.e., Hiera, for real-time ultrasound image segmentation. Including DINOv2 feature representations, the system improves visual expressiveness and manages well with low supervision configurations. It achieves cutting-edge cardiac and thyroid dataset performance, with a priority on scalability and reduced annotation costs.

Li et al. [15] introduced ASTN, a segmentation model that addresses generalization issues across different ultrasound scanners and clinical protocols. The method employs a. latent semantic feature co-registration module for the intent on the lesion region, enhancing robustness. It significantly improves segmentation accuracy and consistency across various clinical imaging conditions.

Wang et al. [16] introduced a multi-view self-supervised learning paradigm in conjunction with two-stage pre-training technique for improving thyroid ultrasound diagnosis. Capitalizing on unlabeled data and diverse opinions, the model learns strong diagnostic features. This approach fortifies prediction performance and minimizes dependence on large annotated datasets.

Li et al. [17] proposed CSASN, an attention-based multitask model for heterogeneous thyroid carcinoma classification in ultrasound images. A feature ex- tractor with a dual-branch with EfficientNet and ViT, the model has a cascaded channel-spatial attention module and a residual multiscale classifier. It is stable and accurate with good performance on rare subtypes and class imbalance.

Alshahad et al. [18] offered an improved Pix2pix GAN thyroid nodule segmentation model to handle data scarcity and instability of GAN training. Adding a supervised component to the generator makes the model generate more accurate and realistic segmentation masks. This breakthrough offers better performance in medical image segmentation in low data scenarios.

Dai et al. [19] have explained the challenge in diagnosing uncommon subtypes of thyroid cancer by creating a text-initiated diffusion framework for producing synthetic images. It integrates clinical experience to develop representative samples of uncommon cases, much improved diagnostic accuracy. It enhances model diversity and stability, reducing the effect of sparsely distributed training data for uncommon cancers.

Yetginler et al. [20] constructed a more improved V-Net model optimized for thyroid nodule segmentation of ultrasound images. Architectural extensions to the baseline V-Net allow clearer definition of nodule borders, preferring enhanced diagnosis and planning of treatment. This study adds the production of precise and computerized instruments for early thyroid disease screening

Kumar et al. [21] described the incorporation of deep learning with ultra- sound imaging to increase thyroid nodule evaluation. Their work demonstrates that sophisticated computational methods holds the potential for enhanced di- agnostic performance and efficiency, facilitating clinical decision-making. The strategy holds potential for reducing unnecessary biopsies and enhancing patient management according to more accurate nodule characterization.

Weng et al. [22] have confirmed a deep model for thyroid nodule classifi- cation using an independent data set compared to the expert radiologists. The study demonstrated that the algorithm could identify and classify nodules based on double ultrasound images. This external validation emphasizes the model's generalizability and potential practical application.

Adam et al. [23] presented STACT-Time, a spatiotemporal cross-attention network for cine thyroid ultrasound time series classification. With learning temporal and spatial features from ultrasound videos, the performance of risk stratification is improved and unnecessary biopsies are reduced. It accomplishes ad- dresses interobserver variation in conventional TI-RADS-based diagnoses.

Wang et al. [24] suggested a clinical-inspired detection framework that mimics radiologist thinking through a feature feedback mechanism. The model has a feedback feature. selection module and feature feedback pyramid for enhancing lesion detection. This approach minimizes noise and blur-induced artifacts in ultrasound images, resulting in better detection precision of thyroid lesions.

Xu et al. [25] studied the application of deep transfer learning with conventional machine learning techniques for benign and malignant thyroid nodule classification. The method comprised preprocessing, LASSO feature selection, and model combination, with assessment by AUC, calibration plots, and DCA. The findings highlight enhanced accuracy and clinical relevance to thyroid diagnosis.

Kim et al. [26] evaluated the performance of CNN-based architectures like ResNet, DenseNet, and EfficientNet for multi-view ultrasound thyroid nodule classification images. The study identifies both the diagnostic advantages and clinical deployment issues of deep learning. It offers main points for the intro- duction of AI into routine thyroid evaluation.

Choi et al. [27] had performed a validation study on federated thyroid ultra- sound image analysis learning to maintain patient privacy. The method allows decentralized training through healthcare facilities without infringing on confidential information. This technique has shown encouraging diagnostic accuracy while talking about clinical data security and privacy environments.

Xu et al. [28] provided a systematic review of the latest developments in the use of artificial intelligence in managing thyroid conditions. The article discusses AI developments in diagnosis, treatment planning, and prognosis prediction in a variety of thyroid diseases. It notes growing trends and directions, highlighting AI's revolutionizing capacity to enhance clinical procedures and patient out- comes.

Li et al. [29] suggested a Human Understandable Thyroid Ultrasound Imaging AI Report System to fill the gap the difference in interpretability between clinicians and AI diagnoses. By creating transparent, clinician-readable reports, the system enhances trust and facilitates AI integration with medicine decision- making. The study emphasizes the importance of explainability to facilitate greater use in clinical practice.

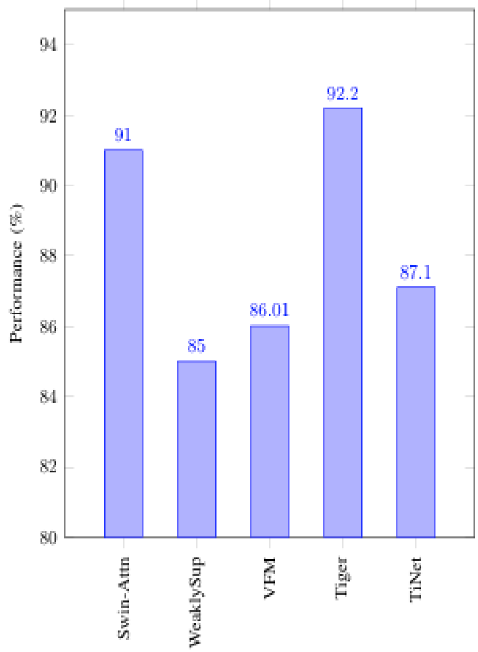

Figure 1. Performance comparison of top 5 peer-reviewed models: Swin-Attn = Swin-Attention Segmentation, VFM = Vision Foundation Model, Tiger = Diffusion-based model, TiNet = Human-interpretable system.

Comparative Review Methodology

This study adopts a systematic comparative review methodology to analyze recent deep learning approaches for thyroid cancer detection using ultrasound imaging. Unlike experimental studies, this work does not involve model implementation, training, or re-evaluation. Instead, performance metrics, datasets, and architectural characteristics are reported as described in the original peer-reviewed publications. The reviewed models were selected based on the following criteria:

- Publication between 2020 and 2025
- Peer-reviewed articles published in Scopus-indexed journals or reputed conferences
- Use of ultrasound imaging for thyroid nodule segmentation or classification
- Demonstrated clinical relevance, innovation, or large-scale validation
- Availability of quantitative performance metrics

Based on these criteria, five representative deep learning paradigms were identified: Swin-Attention Segmentation, Weakly Supervised Segmentation, Vision Foundation Models, the Tiger diffusion-based model, and TiNet. Each model was analyzed across the following dimensions:

- Architectural design: Attention mechanisms, transformer integration, generative modeling and explainability features
- Dataset characteristics: Dataset size, diversity, and multi-center usage as reported by original authors
- Performance metrics: Dice score, AUC, F1-score, inference speed, and clinician agreement
- Interpretability: Availability of explainable outputs such as attention maps or structured reports
- Deployment readiness: Real-time inference capability and clinical workflow compatibility

The review emphasizes clinical applicability and translational readiness rather than raw performance alone. Comparative tables and thematic analysis are used to highlight strengths, limitations, and emerging trends across models. This structured framework enables a consistent and clinically meaningful comparison, facilitating clearer insights into the current state and future direction of deep learning-based thyroid cancer diagnosis.

Table 1. Comparative Summary of Top 5 Peer-Reviewed Deep Learning Models in Thyroid Ultrasound

Model	**Dataset(s)**	**Performance**
Swin-Attention Segmentation	TN3K, DDTI	Dice 90%
Weakly Supervised Framework	TN3K, Surgical Data	Dice 85%
Vision Foundation Model (VFM)	TN3K, Stanford, TG3K	86.01% Dice, 77 FPS
Tiger Model	186K images, 10 hospitals	92.2% Fooling Rate
TiNet	10K images, 4 hospitals	87.1% clinician agreement

Gap Analysis

While the reviewed methodologies illustrate impressive progress in thyroid nodule segmentation and classification, they also expose several critical gaps that continue to limit the widespread clinical adoption and reliability of these models. These gaps span six core domains: generalizability, rare subtype recognition, interpretability, deployment feasibility, multimodal integration, and benchmarking. In terms of generalizability, most models report high internal validation performance but fall short when evaluated across diverse in situations, imaging devices, and acquisition protocols. Despite the use of multiple datasets in some cases, true multi-center generalization is rarely achieved. Without standardized data collection protocols and broad external validation, models risk overfitting to dataset-specific artifacts and may not translate well in real-world clinical scenarios.

Handling of rare thyroid subtypes remains inadequate across most models. While the Tiger model provides an innovative approach using diffusion-based image synthesis for underrepresented malignancies, the majority of AI systems continue to focus on common types like papillary thyroid carcinoma. As a result, important variants such as follicular, medullary, and anaplastic thyroid cancers are often misclassified or over looked entirely. There is a pressing need for more curated, balanced datasets and tailored model training for rare subtype detection. Interpretability is another persistent shortfall. Al though TiNet has made strides in producing structured, human readable diagnostic reports, most high-performing models still operate as opaque black boxes. Standard tools such as Grad-CAM and attention maps are often insufficient to meet regulatory explainability requirements. Furthermore, few studies include clinician usability evaluations or prioritize interpretability in their core design. Performance feasibility remains a trade-off with many of the most accurate models employing computationally intensive architectures, such as large Transformers or dual-stage pipelines. Although the Vision Foundation Model demonstrates real-time capability with 77 FPS, such efficiency is an exception rather than the norm. High complexity hinders deployment in resource-limited environments like rural clinics or mobile screening setups. Multimodal integration is also largely underdeveloped. While TiNet shows initial promise in aligning diagnostic outputs with structured TI-RADS reporting, most systems still rely solely on imaging data. The integration of clinical metadata—such as lab tests, patient history, or genetic markers—could offer a more holistic diagnostic perspective that mirrors the approach taken by experienced endocrinologists.

Finally, benchmarking practices are inconsistent. Most seg mentation models rely solely on Dice scores, while classification models often omit key diagnostic metrics such as AUC, F1-score, sensitivity, and specificity. This lack of standardized reporting hinders meaningful comparisons across studies and limits their clinical interpretability. Only a small number of peer-reviewed models outside the top five offer comprehensive evaluations (see Table 2). Addressing these challenges will require interdisciplinary collaboration among clinicians, data scientists, and engineers to advance beyond prototypes and deliver AI tools that are transparent, generalizable, and robust in real-world healthcare environments.

Table 2. Deep Learning Models with Clinically Relevant Metrics (AUC, F1-score, Sensitivity)

Model	Year	Primary Task	AUC	F1 / Sensitivity / Specificity	Dataset
Ensemble DL Classifier	2020	Classification	0.960	F1 = 0.95, Sens = 0.93	Multi-center ultrasound dataset
Deep Transfer Learning CNN	2023	Classification	0.940	F1 = 0.93, Sens = 0.91, Spec = 0.92	Private hospital dataset
Multi-Scale CNN Model	2023	Classification	0.910	F1 = 0.90, Sens = 0.89, Spec = 0.90	Sick-euthyroid dataset (UCI)
2D US Image Classifier	2022	Classification	0.920	F1 = 0.92, Sens = 0.90	Public clinical ultrasound data
Multi-Attribute Attention Network	2024	Classification + Explainability	0.930	Sens = 0.92, Spec = 0.91	TN3K dataset

Benchmarking Clinical Metrics

While Dice score remains the primary metric reported for segmentation-focused models such as Swin-Attention, Weakly Supervised Segmentation, and VFM, most of the top performing models do not consistently report classification metrics such as AUC, F1-score, sensitivity, or specificity. This inconsistency in clinical metric reporting limits the ability to conduct standardized comparisons across models, particularly for those addressing diagnostic classification tasks. Furthermore, computational complexity and inference latency are often underreported, with the Vision Foundation Model (VFM) being a notable exception, achieving 77 FPS in real-time deployment settings. To highlight this gap, we include several additional models from the broader landscape that demonstrate strong clinical benchmarking using more comprehensive evaluation metrics, as summarized in Table 2 metrics: refer to table 2.

These models demonstrate the benefits of reporting com prehensive diagnostic metrics, which enable more clinically meaningful evaluations. Their performance provides a valuable contrast to the top 5 models and illustrates the importance of incorporating AUC, F1, and sensitivity in future work.

Segmentation remains the most studied task in thyroid ultrasound imaging. Traditional encoder-decoder architectures, especially U-Net and its derivatives, have been widely adopted for localizing nodules within ultrasound scans. Among the peer-reviewed models, the Swin-Attention Segmentation framework introduces Transformer-inspired attention mechanisms within a hierarchical encoder-decoder, achieving state of-the-art Dice scores above 90% on the TN3K and DDTI datasets. The Weakly Supervised Segmentation framework offers an alternative with minimal annotation dependency, leveraging high-confidence label generation and rationality guided loss functions to achieve competitive performance (Dice >85%).

The Vision Foundation Model, however, is both peer reviewed and deployable, integrating pretrained encoders (DI NOv2, Hiera) to support real-time segmentation across multi institution datasets at 77 FPS, underscoring a new frontier in rapid, scalable AI imaging. Taken together, these thematic clusters highlight the diversification of AI applications in thyroid ultrasound imaging. While segmentation and classification remain foundational tasks, the field is rapidly evolving toward multimodal, explainable, and deployable solutions that align more closely with clinical workflows and decision-making patterns.

Conclusion

The application of deep learning to thyroid ultrasound imaging has matured beyond isolated performance improvements toward a broader focus on clinical relevance, interpretability, and deployment feasibility. This comparative review examined five representative and peer-reviewed deep learning paradigms—Swin-Attention Segmentation, Weakly Supervised Segmentation, Vision Foundation Models, the diffusion-based Tiger Model, and the interpretable TiNet framework—each illustrating a distinct methodological direction in thyroid cancer detection.

The analysis reveals that while attention-based and transformer-driven architectures achieve high segmentation accuracy, their clinical translation is often limited by computational complexity and lack of interpretability. Weakly supervised methods effectively reduce annotation burden but may compromise robustness across heterogeneous clinical settings. Vision Foundation Models represent a promising balance between accuracy and efficiency, demonstrating real-time performance and scalability across institutions. Diffusion-based approaches extend diagnostic capability to rare thyroid cancer subtypes, addressing a critical but underexplored challenge. In contrast, TiNet emphasizes explainability and structured reporting, highlighting the importance of human-aligned AI systems in fostering clinician trust.

Despite these advances, several challenges persist, including limited multi-center generalization, inconsistent reporting of clinically meaningful metrics, inadequate handling of rare malignancies, and insufficient integration into existing clinical workflows. Addressing these limitations requires future research to prioritize standardized benchmarking, external validation, explainable decision pathways, and regulatory-aware system design.

From a translational perspective, this review consolidates fragmented advancements into a clinically oriented comparative framework, offering guidance for researchers and practitioners seeking deployable and trustworthy AI solutions for thyroid cancer diagnosis. By aligning technical innovation with real-world clinical needs, deep learning systems can evolve from experimental tools into reliable diagnostic partners within modern thyroid healthcare.

Clinical Validation

While significant advances have been made in applying deep learning to thyroid ultrasound imaging, the path from academic research to real-world clinical deployment requires careful planning and multi-stakeholder coordination. This section outlines a practical roadmap to bridge that gap. The first step in volves rigorous multi-center validation. Most existing models are evaluated on internal or single-institution datasets, limiting their generalizability. To ensure robustness across diverse clinical settings, prospective validation must be conducted using data from different populations, imaging equipment, and institutions. Approaches such as federated learning and cross center benchmarking can help mitigate overfitting and domain shift, enabling models to perform reliably in heterogeneous environments.

The smooth incorporation of AI into clinical workflows is equally crucial. Models should be integrated into radiology infrastructure, such as Radiology Information Systems (RIS) or Picture Archiving and Communication Systems (PACS), for practical implementation. This calls for the creation of user-friendly interfaces that support standardized formats such as TI-RADS, tools that help clinicians interact with AI outputs, and automatic annotation overlays. Early in the development process, ethical and regulatory issues must also be addressed. Clinical-grade models must comply with regulatory frame works like the European CE marking or the 510(k)-clearance procedure of the U.S. FDA.

Furthermore, patient data must be managed in accordance with privacy regulations such as GDPR or HIPAA, especially in federated learning scenarios that entail decentralized data sharing. Collaboration between humans and AI is yet another crucial component of clinical adoption. Transparency and interpretability are key components of trust in AI-assisted diagnostics. Models should produce outputs that are easy to understand, like heatmaps with calibrated confidence scores or structured reports that are aligned with TI-RADS. An encouraging example of AI tools created with clinician usability in mind are systems such as TiNet.

Last but not least, for widespread deployment—particularly in low-resource or mobile ultrasound scenarios—edge optimization and real-time inference are essential. For practical deployment, inference efficiency must be achieved without compromising accuracy. The potential of high-speed, low latency solutions appropriate for bedside or rural applications is demonstrated by models such as the Vision Foundation Model, which runs at 77 FPS. When taken as a whole, these translational steps are crucial to bringing deep learning systems into the clinical mainstream as reliable, safe, and efficient thyroid imaging diagnostic tools.

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