AI-Powered Precision Diagnosis of Thyroid Anomalies in Ultrasound Scans

K K Lokeswaran[1], T Anil Kumar[2], G Swapna[3] , G Viswanath[4]

[1]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: lokeswaran.kk@gmail.com , ORCID-ID: 0009-0002-7740-548X

[2]Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: anil.thumburu@gmail.com , ORCID-ID: 0009-0003-3312-3031

[3]Assistant Professor, Apollo institute of pharmaceutical sciences, The Apollo University, Chittoor, IndiaEmail: swapnagv111@gmail.com , ORCID-ID: 0000-0002-9340-4148

[4]Associate Professor, Dept. of AI & ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: viswag111@gmail.com , ORCID-ID: 0009-0001-7822-4739

Area/Section: Engineering with Medical Background
Type of the Paper: Regular Paper
Type of Review: Peer Reviewed as per |C|O|P|E| guidance.
Indexed in: OpenAIRE.
DOI: https://doi.org/10.5281/zenodo.15495261
Google Scholar Citation: IJHSP

How to Cite this Paper:

Lokeswaran, K. K., Kumar, T. A., Swapna, G. & Viswanath, G.(2025). AI-Powered Precision Diagnosis of Thyroid Anomalies in Ultrasound Scans. *International Journal of Health Sciences and Pharmacy (IJHSP)*, *9*(1), 160-169. DOI: https://doi.org/10.5281/zenodo.15495261

International Journal of Health Sciences and Pharmacy (IJHSP)
A Refereed International Journal of Srinivas University, India.

Crossref DOI: https://doi.org/10.47992/IJHSP.2581.6411.0139

Received on: 16/04/2025
Published on: 23/05/2025

International Journal of Health Sciences and Pharmacy (IJHSP), ISSN: 2581-6411, Vol. 9, No. 1, May 2025

SRINIVAS PUBLICATION

AI-Powered Precision Diagnosis of Thyroid Anomalies in Ultrasound Scans

K K Lokeswaran[1], T Anil Kumar[2], G Swapna[3] , G Viswanath[4]

[1]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur,

Email: lokeswaran.kk@gmail.com , ORCID-ID: 0009-0002-7740-548X

[2]Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: anil.thumburu@gmail.com , ORCID-ID: 0009-0003-3312-3031

[3]Assistant Professor, Apollo institute of pharmaceutical sciences, The Apollo University, Chittoor, IndiaEmail: swapnagv111@gmail.com , ORCID-ID: 0000-0002-9340-4148

[4]Associate Professor, Dept. of AI & ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: viswag111@gmail.com , ORCID-ID: 0009-0001-7822-4739

ABSTRACT

The increasing global prevalence of thyroid cancer has created an urgent need for enhanced diagnostic precision in thyroid anomaly detection through ultrasound scans. Manual interpretation of thyroid nodules in ultrasound images often poses challenges for radiologists due to factors such as overlapping tissues, low image contrast, and the presence of small or indistinct nodules. In response to this diagnostic complexity, an AI-powered computer-aided diagnosis (CAD) system has been developed to automate and refine the identification of thyroid anomalies. The system is designed to significantly aid radiologists in making timely and accurate decisions by leveraging advanced deep learning methodologies.A publicly accessible thyroid ultrasound imaging dataset was employed for model training, validation, and evaluation. The dataset encompasses a diverse array of sonographic thyroid nodules, including benign and malignant samples. To effectively detect and classify these nodules, object detection algorithms were implemented, with particular focus on the YOLO (You Only Look Once) framework. The model variant YOLOv5x6 was chosen due to its capacity to perform high-speed and high-precision detection. Multiple optimization strategies were incorporated to improve performance: enhanced feature extraction for learning complex patterns, data augmentation for better generalization, and class imbalance rectification using oversampling and weighted loss functions. In addition, the model architecture was fine-tuned to boost sensitivity in identifying small and overlapping nodules.Among the evaluated models, YOLOv5x6 achieved superior performance with a precision of 0.561, recall of 0.835, and a mean average precision (mAP) of 0.650. These results highlight the robustness and reliability of the system in detecting thyroid nodules across varied sonographic conditions. The integration of artificial intelligence into medical imaging workflows demonstrates the potential to accelerate diagnostic processes, minimize oversight, and enhance overall clinical outcomes. This diagnostic tool offers a dependable solution that aligns with the growing demand for accurate, efficient, and automated thyroid anomaly detection in the healthcare domain.

Keywords: Computer-aided diagnosis, thyroid nodules, ultrasound, YOLOv5 network, attention module, label smoothing

1. INTRODUCTION:

Thyroid nodules are prevalent tumors in adults, with a markedly extra prevalence in girls, who are round three instances more likely than men to get a diagnosis of thyroid cancer [1]. In latest decades, the prevalence of thyroid cancer has significantly escalated, having quadrupled or extra in many high-income nations [2], [3]. This increase underscores the significance of early identity and specific assessment of thyroid irregularities. Thyroid nodules regularly represent the initial signs of thyroid most cancers, necessitating the differentiation among benign and malignant nodules to enhance affected person analysis and survival rates [4].

Ultrasonography has emerged as a principal modality for the evaluation of thyroid nodules thanks to its non-invasive, non-radioactive, and cost-effective characteristics, rendering it readily available for popular clinical application. It facilitates the imaging of thyroid systems and aids in the detection of any abnormalities [5]. Even though ultrasonography efficiently identifies thyroid nodules, differentiating between benign and malignant nodules is a large task for radiologists due to the range in nodule characteristics and the intricacy of ultrasound images.

Progress in computer-aided diagnosis systems, especially those utilizing machine learning and deep learning algorithms, significantly enhances the accuracy, efficiency, and rapidity of thyroid nodule detection. These technologies can aid radiologists by automating the analysis of ultrasound images and detecting possibly malignant nodules, thereby minimizing diagnostic errors and facilitating early intervention for improved patient outcomes.

2. OBJECTIVES:

This AI-powered diagnostic system aims to assist radiologists in detecting thyroid anomalies with improved accuracy using ultrasound scans. Its key goals focus on precision, efficiency, and clinical applicability.

(1)To develop a deep learning-based computer-aided diagnosis system

That accurately identifies and localizes thyroid nodules in ultrasound scans using object detection techniques like YOLOv5x6, with optimization for small and overlapping nodules.

(2)To improve model robustness through data-centric strategies

Including the use of a diverse, publicly available thyroid ultrasound dataset, advanced feature extraction, data augmentation, and class imbalance handling techniques for generalized performance.

(3)To evaluate diagnostic performance using critical metrics

Such as "precision, recall, and mean average precision (mAP)", ensuring the model supports radiologists with high sensitivity and specificity in clinical thyroid anomaly detection.

3. REVIEW OF LITERATURE/ RELATED WORKS:

Thyroid cancer is among the most prevalent malignancies in adults, especially women, with a notable rise in its frequency in current decades. Timely identification and specific categorization of thyroid nodules, which may be benign or cancerous, are essential for enhancing patient outcomes. Ultrasound imaging is an established, non-invasive, and economical approach for screening thyroid nodules. Despite the fact that, exactly differentiating among benign and malignant nodules continues to be tough, requiring the implementation of "computer-aided analysis (CAD)" systems. Latest breakthroughs in "machine learning (ML) and deep learning (DL)" methodologies have yielded substantial enhancements in the detection, segmentation, and type of thyroid nodules from ultrasound snap shots.

Severa research projects have investigated the usage of "deep learning" strategies for thyroid nodule analysis in ultrasound snap shots. Yang et al. (2024) delivered a greater "convolutional neural network (CNN)"-based algorithm for thyroid nodule screening. This model improves the detection accuracy of thyroid nodules through a multi-scale feature extraction method, which captures each intricate info and wider contextual records from ultrasound pics [20]. Their studies emphasizes improving the version's robustness through tackling the issues of small-sized nodules and inconsistent picture features, widespread in actual-world situations.

Vahdati et al. developed a deep learning model with several scores for detection and characterisation of thyroid knots in ultrasound images, (2024). This model employs many views of the identical image to seize the distinct houses of nodules, hence improving its accuracy in detection and classification as benign or malignant [7]. The multi-view technique effectively addresses the challenges presented by using the vast variability in shapes, textures, and sizes of thyroid nodules, hence enhancing the model's generalization across various ultrasound datasets.

A significant study via Gunes et al. (2024) concentrated on the segmentation of thyroid nodules in ultrasound imagery. They utilized a DL-based segmentation method able to precisely isolating nodules from adjacent thyroid tissue. This segmentation is vital for next classification responsibilities, as it facilitates the precise delineation of nodule barriers, which is essential for proper analysis and remedy planning [22]. Their technique exhibited significant sensitivity in identifying diverse nodule sorts, including irregularly shaped nodules and those that intersect with adjacent tissues.

Deep learning algorithms have been hired to concentrate on particular characteristics of thyroid nodules. Chen et al. (2023) utilized “deep learning” methodologies to detect calcification and colloid in thyroid nodules, which are critical indications for differentiating malignant from benign nodules. The potential to autonomously recognize these traits markedly decreases the time wished for radiologists to evaluate nodules and enhances diagnostic precision [9]. Their algorithm accurately identified calcification and colloid characteristics, indicating that “deep learning”fashions can appreciably enhance the interpretability of ultrasound photos.

Kunapinun et al. (2023) investigated the application of "Generative adversarial Networks (GANs)" to enhance learning dynamics for thyroid nodule segmentation. They introduced an innovative GAN architecture that improves the segmentation precision of thyroid nodules with the aid of growing synthetic pictures to augment the version's training. This method addresses challenges including statistics scarcity and class imbalance, which frequently obstruct the efficacy of deep gaining knowledge of models in clinical picture analysis. The GAN-based method exhibited better segmentation results, especially for small and irregularly shaped nodules [24].

Similarly, Li et al. (2023) presented an innovative approach for the segmentation of thyroid nodules making use of ultrasound pictures. Their technique utilized a hybrid DL architecture that integrated "convolutional neural networks (CNNs)" with fully connected layers, attaining great accuracy in segmenting thyroid nodules from elaborate ultrasound pics. This method enhances the localization and identity of nodules, which is essential for proper diagnoses. Their research discovered that the integration of diverse deep learning methodologies can enhance outcomes in thyroid nodule segmentation, especially for images characterized by way of low evaluation or noise [11].

Zhou et al. (2022) introduced a streamlined deep learning network for the automated detection and identity of thyroid nodules in ultrasound pictures. Their model is engineered for velocity and precision, rendering it suitable for real-time applications in clinical environments. By means of concentrating on lowering the computational complexity of the network, they attained speedy processing even as maintaining brilliant accuracy. This is especially crucial for clinical processes when time is of the essence, because the model aids radiologists in promptly detecting probable malignant nodules for extra examination [26]. The network's lightweight design renders it suitable for implementation on devices with confined processing talents, including cell devices and edge computing systems.

In the end, Shahroudnejad (2021) introduced a fully automated system for the detection, segmentation, and classification of thyroid nodules utilizing DL and image processing methodologies. This system consolidates various stages of the diagnostic process, encompassing the detection and segmentation of nodules, accompanied by their classification as benign or malignant. The model utilizes a mixture of "convolutional neural networks (CNNs)" for feature extraction and "support vector machines (SVM)" for category, attaining first rate accuracy and resilience in identifying thyroid disorders. The research underscores the capability of completely automated systems to aid radiologists and physicians by assuaging their workload and improving diagnostic precision [13].

The improvements in "deep learning and machine learning" processes have markedly superior the accuracy and efficiency of thyroid nodule detection in ultrasound pix. Through tackling issues consisting of class imbalance, small or overlapping nodules, and inconsistent imaging quality, these strategies have improved the accuracy of thyroid nodule classification, doubtlessly diminishing the dependence on invasive biopsy strategies. As those models advance, they provide significant capability for enhancing diagnostic workflows in medical practice, resulting in earlier analysis, superior treatment planning, and improved patient outcomes.

Table 1: Literature Survey Comparison Table

Sl. No	Area & Focus of the Research	The result of the Research	Reference
1	CNN-based multi-scale feature extraction for thyroid nodule detection.	Improved accuracy in small nodule detection and feature robustness.	Yang, T. Y., Zhou, L. Q. et. al..,(2024). [20]
2	Multi-view deep learning model for nodule classification accuracy.	Enhanced generalization and benign/malignant classification precision.	Vahdati, S., Khosravi, B., Robinson et. al., (2024) [7]
3	Segmentation of thyroid nodules using deep learning techniques.	High sensitivity in detecting complex and irregular nodules.	Gunes, B. B., Samlı, R., Dogan et.al, (2024) [22]
4	Detection of calcification and colloid via deep learning.	Improved interpretability and diagnostic speed for radiologists.	Chen, C., Liu, Y., Yao et.al (2023) [9]
5	GANs for enhancing segmentation through synthetic image generation.	Boosted segmentation accuracy for small and imbalanced datasets.	A. Kunapinun, M. N. Dailey, D. Songsaenget.al. (2023) [24]

4. MATERIALS AND METHODS:

The suggested method aims to automate the detection of thyroid nodules in ultrasound pictures, responding to the growing call for for accuracy and performance in sonographic diagnosis. It integrates state-of-the-art item detection algorithms, such as "SSD, RetinaNet, faster R-CNN, YOLOv5, YOLOv8, YOLOv9", and augmented iterations of YOLOv5 featuring Label "Smoothing Regularization (LSR), Coordinate attention Mechanism (CAM), and their amalgamation (LSR CAM)". These strategies are utilized to reinforce detection precision, rectify class imbalances, and refine feature extraction.

The approach seeks to address difficulties including identifying small, overlapping nodules and enhancing the model's overall robustness thru the integration of several strategies. A publicly accessible thyroid ultrasonography dataset is applied for training and validation, incorporating pre-processing approaches to assure data quality and diversity. This thorough technique equips radiologists with a dependable tool for the powerful identification of thyroid abnormalities, alleviating diagnostic burdens while guaranteeing particular and prompt detection of dangerous malignant nodules.

Fig 1: Proposed Architecture

The system architecture illustrated in the image (Fig. 1) the depicted system architecture delineates a radical framework for item detection in medical imaging. The process commences with the procurement of a dataset of clinical photos. The dataset undergoes image processing and data augmentation techniques to improve its quality and diversity. Thereafter, the pre-processed data is input into various item detection models, including "SSD, RetinaNet, faster R-CNN, YOLOv5, and its variations enhanced with LSR and CAM". The efficacy of these models is meticulously assessed to determine the optimal method for particular object detection in medical picture analysis.

4.1 Dataset Collection:

The thyroid nodule identification dataset comprises 176 ultrasound pictures obtained from diverse medical sources. The photos were acquired from patients diagnosed with thyroid issues, encompassing each benign and malignant nodules. The dataset encompasses an expansion of nodule sizes, forms, and attributes, imparting a radical portrayal of real ultrasound imaging situations. The photos are categorised to indicate the presence, nature, and place of the nodules, facilitating particular training and evaluation of "deep learning' models. This dataset is crucial for the improvement and assessment of computerized methods for the detection and categorization of thyroid nodules.

4.2 Pre-Processing:

Pre-processing is an essential phase in dataset preparation for model training, encompassing the conversion of pictures into an appropriate format, the software of transformations, and the assurance of statistics consistency to enhance performance.

4.2.1 Image Processing

Image processing encompasses multiple stages to ready ultrasound images for model training. The image is initially transformed into a blob object to ensure compatibility with neural network enter. Subsequently, the class and bounding boxes are mounted for annotation. The photo array is transformed into a NumPy array for processing. In photo processing, the image is blended with its appropriate annotation document, and the image is transformed from BGR to RGB format. A mask is generated to emphasise regions of hobby, and the image is enlarged to conform to the model's specified input dimensions, guaranteeing appropriate scaling and alignment for training.

4.2.2 Data Augmentation

Data augmentation is employed to synthetically enlarge the dataset and enhance model resilience. This entails randomly modifying the pics by transformations like rotation, flipping, and shifting. These approaches introduce changes in the image, mitigating the risk of overfitting and enhancing the version's ability to generalize to unfamiliar data. Images are randomly cropped, rotated at many angles, and enlarged to assure a variety of education examples. Those enhanced pictures replicate numerous real-global situations, including alterations in perspective and illumination, guaranteeing the model's capability to control discrepancies during detection. Facts augmentation improves the model's capacity to perceive thyroid nodules under diverse situations, hence enhancing overall detection accuracy.

4.3 Algorithms:

SSDis utilized for real-time object detection, facilitating swift identification of thyroid anomalies in ultrasound pics. Its efficacy enables radiologists to swiftly evaluate potential malignant areas during diagnosis.

RetinaNetis employed to rectify class imbalance in detection tasks, hence improving the precision of thyroid cancer identification. The focal loss function enhances the detection efficacy of small and overlapping nodules.

FasterRCNN[14]achieves superior precision in item detection with the mixing of vicinity proposal networks and deep learning techniques. It correctly recognizes and categorizes thyroid nodules, helping radiologists in precise diagnosis.

YOLOv5functions as an efficient and fast object detection model, delivering real-time analysis of thyroid ultrasound pictures. Its ability to simultaneously come across many objects enhances universal diagnostic efficiency.
YOLOv5 with Label Smoothing Regularizationimproves the model's resilience by mitigating overfitting. This enhances detection accuracy for thyroid disorders, hence bolstering radiologists' confidence in their findings.
YOLOv5 with Coordinate Attention Mechanismconcentrates on essential characteristics in thyroid ultrasound pictures. This improves detection accuracy by highlighting critical spatial information, facilitating more precise identification of anomalies.
YOLOv5 + LSR CAM: [15]the integration of "LSR and CAM with YOLOv5" enhances both robustness and feature extraction. This comprehensive method improves detection efficacy for thyroid cancer, facilitating better informed diagnostic choices.
YOLOv8utilized for its detection abilities, enhancing each speed and precision in finding thyroid problems. This version facilitates thorough analysis, aiding radiologists in their diagnostic procedures.
YOLOv5x6is utilized for its sophisticated architecture, enhancing the identification of tiny thyroid nodules. The improved feature representation aids radiologists in attaining more accuracy within the location and categorization of probable malignant areas.
YOLOv9is incorporated for its recent developments in item detection, offering enhanced accuracy and speed in thyroid cancer diagnosis. Its use enables prompt and particular diagnostic results for radiologists.

5. RESULTS AND DISCUSSION:

Precision: The accuracy evaluates the share of precisely classified cases among cases identified as positive. As a result, the formula for calculating accuracy is expressed:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (1)"$$

Recall: The reminder is a computation in "machine learning" that assesses the version's capacity to recognise all pertinent associations with the chosen magnificence. These are the ratios of exactly almost positive remarks for general actual positivity and they offer understanding of model performance in spotting the presence of a chosen class.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} (2)$$

mAP:"Average average accuracy (MAP) "is statistics for optimum evaluation assessment. It assesses their placement and the quantity of pertinent suggestions on the list. The map on K is meant to be an arithmetic for all users or enquiries' impulse of the “Village Recision (Ap)” in OK.

$$"mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k (3)"$$

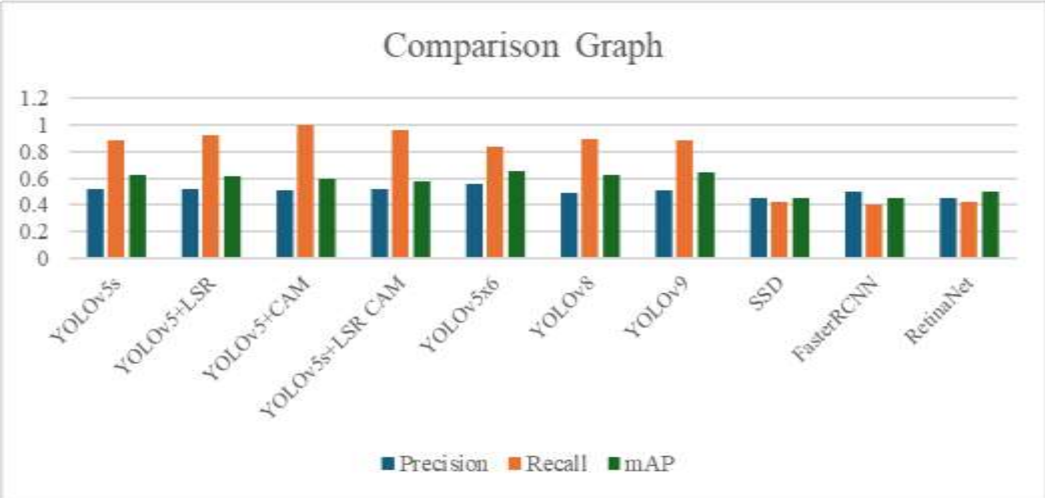
Table (1) Assessment of power metrics - "accuracy, evocation, average average accuracy (map)" - for each algorithm.Yolov5x6 regularly exceeds all other algorithms in all measures. The tables offer a comparative examination of metrics for alternative methods.

Table 2: Performance Evaluation Table

Model	Precision	Recall	mAP
YOLOv5s	0.514	0.884	0.628
YOLOv5+LSR	0.516	0.923	0.619
YOLOv5+CAM	0.509	1.000	0.596
YOLOv5s+LSR CAM	0.521	0.962	0.574
YOLOv5x6	**0.561**	**0.835**	**0.650**

YOLOv8	0.492	0.898	0.627
YOLOv9	0.511	0.885	0.642
SSD	0.449	0.420	0.449
FasterRCNN	0.500	0.407	0.449
RetinaNet	0.449	0.425	0.500

Graph 1: Comparison Graphs



Graph (1) displays accuracy in blue, memory in orange, and mapping in green colours. "Yolov5x6" outperforms all other models in every category and gets the best values. The above grain visually reflects these results.

6. CONCLUSION:

In conclusion, the suggested system illustrates the efficacy of sophisticated item detection methodologies for automating the identification of thyroid nodules in ultrasound pix. Of the assessed models, YOLOv5x6 demonstrated the advanced performance, attaining a precision of zero.561, a recall of 0.835, and a "mean average precision (mAP)" of zero.650. This exceptional performance underscores the model's capacity to properly pick out thyroid abnormalities, particularly in difficult situations including small or overlapping nodules. The amalgamation of YOLOv5 with "Label Smoothing Regularization (LSR) and Coordinate attention Mechanism (CAM)" significantly augmented its resilience, resulting in a more dependable system for clinical applications. The results underscore the proposed system's capacity to aid radiologists in figuring out thyroid cancer with extra efficiency and accuracy, thus alleviating diagnostic burdens and enhancing overall clinical strategies. The system utilizes high-performance algorithms to decorate thyroid cancer detection, providing set off and accurate identification of anomalies.

The future potential of the automated computer-aided diagnosis platform for thyroid cancer detection is clear in various promising avenues. Integrating supplementary deep gaining knowledge of methodologies and sophisticated algorithms can improve detection precision and expand the spectrum of identifiable anomalies. Enhancing the dataset to embody numerous populations and many imaging modalities could boom generalization and robustness. Furthermore, integrating real-time monitoring and telemedicine functionalities can permit remote diagnostics, enhancing accessibility for patients in underserved areas. Future endeavors may also include the integration of explainable AI to clarify selection-making tactics, so fostering transparency and trust in automated systems, ultimately propelling advancements in medical imaging and diagnostics.

REFERENCES:

[1] Lenting, K., Verhaak, R., ter Laan, M., Wesseling, P., & Leenders, W. (2017). Glioma: Experimental models and reality. *Acta Neuropathologica*, 133(2), 263–282.

[2] Swapna, G. (2023). A Drug-Target Interaction Prediction Based on Supervised Probabilistic Classification. *Journal of Computer Science*, 19(10), 1203-1211.

[3] Bray, F., Ferlay, J., Soerjomataram, I., Siegel, R. L., Torre, L. A., & Jemal, A. (2018). Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA, Cancer J. Clinicians*, 68(6), 394–424.

[4] Viswanath, G. (2024). Machine-Learning-Based Cloud Intrusion Detection. *International Journal of Mechanical Engineering Research and Technology*, 16(3), 38-52.

[5] Haugen, B. R. (2017). 2015 American thyroid association management guide lines for adult patients with thyroid nodules and differentiated thyroid cancer: What is new and what has changed?. *Cancer*, 123(3), 372–381.

[6] Swapna, G. & Bhaskar, K. (2024). Malaria Diagnosis Using Double Hidden Layer Extreme Learning Machine Algorithm With Cnn Feature Extraction And Parasite Inflator. International Journal of Information Technology and Computer Engineering, 12(3), 536-547.

[7] Chen, S. L., Chen, T. Y., Huang, Y. C., Chen, C. A., Chou, H. S., Huang, Y. Y., Lin, W. C., Li, T. C., Yuan, J. J., Abu, P. A. R., et al. (2022). Missing Teeth and Restoration Detection Using Dental Panoramic Radiography Based on Transfer Learning with CNNs. *IEEE Access*, 10(2), 118654–118664.

[8] Viswanath, G., & Dr.Swapna, G. (2025). Diabetes Diagnosis Using Machine Learning with Cloud Security. *Cuestiones de Fisioterapia*, 54(2), 417-431.

[9] Chen, C., Liu, Y., Yao, J., Lv, L., Pan, Q., Wu, J., & Xu, D. (2023). Leveraging deep learning to identify calcification and colloid in thyroid nodules. Heliyon, 9(8), 1-9.

[10] Viswanath, G. (2024). Improved Light GBM Model Performance Analysis and Comparison for Coronary Heart Disease Prediction. *International Journal of Information Technology and Computer Engineering*, 12(3), 658-672.

[11] Li, C. F., Du, R. Q., Luo, Q. Y., Wang, R., & Ding, X. H. (2023). A novel model of thyroid nodule segmentation for ultrasound images. *Ultrasound Med. Biol.*, 49(2), 489–496.

[12] Viswanath, G., (2024). Enhancing Cloud Security: A Blockchain-Based Verification Framework for Multi-Cloud Virtual Machine Images. *Frontiers in Health Informatics*, 13(3), 9535-9549.

[13] Estai, M., Tennant, M., Gebauer, D., Brostek, A., Vignarajan, J., Mehdizadeh, M., & Saha, S. (2022). Evaluation of a deep learning system for automatic detection of proximal surface dental caries on bitewing radiographs. *Oral Surg. Oral Med. Oral Pathol. Oral Radiol*. 134(2), 262-270.

[14] Viswanath, G. (2021). Hybrid encryption framework for securing big data storage in multi-cloud environment. *Evolutionary intelligence*, 14(2), 691-698.

[15] Karatas, O., Cakir, N. N., Ozsariyildiz, S. S., Kis, H. C., S. Demirbuga, S., & Gurgan, C. A. (2021). A deep learning approach to dental restoration classification from bitewing and periapical radiographs. *Quintessence Int.*, 52(7), 568–574.

[16] La Vecchia, C., Malvezzi, M., Bosetti, C., Garavello, W., Bertuccio, P., Levi, F., & Negri, E. (2015). Thyroid cancer mortality and incidence: A global overview. *Int. J. Cancer*, 136(9), 2187–2195.

[17] Viswanath, G. (2022). A Smart Recommendation System for Medicine using Intelligent NLP Techniques. *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*, 3(2), 1081-1084.

[18] Park, C. S., Kim, S. H., Jung, S. L., Kang, B. J., Kim, J. Y., Choi, J. J., Sung, M. S., Yim, H. W., & Jeong, S. H. (2010). Observer variability in the sono graphic evaluation of thyroid nodules. *J. Clin. Ultrasound*, 38(6), 287–293.

[19] Swapna, G., & Bhaskar, K. (2024). Early-Stage Autism Spectrum Disorder Detection Using Machine Learning. *International Journal of HRM and Organizational Behavior*, 12(3), 269-283,

[20] Muramatsu, C., Morishita, T., Takahashi, R., Hayashi, T., Nishiyama, W., Ariji, Y., Zhou, X., Hara, T., Katsumata, A., Ariji, E., et al. (2021). Tooth detection and classification on panoramic radiographs for automatic dental chart filing: Improved classification by multi-sized input data. *Oral Radiol*, 37(5), 13–19.

[21] Viswanath, G. (2024). Multiple Cancer Types Classified Using CTMRI Images Based On Learning Without Forgetting Powered Deep Learning Models. *International Journal of HRM and Organizational Behavior*, 12(2), 243-253.

[22] Gunes, B. B., Samlı, R., Dogan, M. B., & Yildirim, D. Segmentation Of Thyroid Nodules On Ultrasound Images. *Journal of Naval Sciences and Engineering*, 20(2), 191-211.

[23] Viswanath, G., & Swapna, G. (2024). Health Prediction Using Machine Learning with Drive HQ Cloud Security. *Frontiersin Health Informatics*, 13(8), 2755-2761

[24] Kunapinun, A., Dailey, M. N., Songsaeng, D., Parnichkun, M., Keatmanee, C., & Ekpanyapong, M. (2023). Improving GAN learning dynamics for thyroid nodule segmentation. **Ultrasound Med. Biol.,** 49(2), 416–430.

[25] Viswanath, G., & Swapna, G. (2025). Data Mining-Driven Multi-Feature Selection for Chronic Disease Forecasting. *Journal of Neonatal Surgery*, 14(5s), 108-124.

[26] Zhou, S., Qiu, Y., Han, L., Liao, G., Zhuang, Y., Ma, B., & Chen, K. (2022). A lightweight network for automatic thyroid nodules location and recognition with high speed and accuracy in ultrasound images. *Journal of X-Ray Science and Technology*, 30(5), 967-981.

[27] Viswanath, G. (2024). Personalized Breast Cancer Prognosis through Data Mining Innovations. *Cuestiones de Fisioterapia*, 53(2), 538-548.

[28] Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards real-time object detection with region proposal networks. *IEEE Trans. Pattern Anal. Mach. Intell.*, 39 (6), 1137–1149.

[29] Viswanath, G. (2021). Adaptive Light Weight Encryption Algorithm for Securing Multi-Cloud Storage. *Turkish Journal of Computer and Mathematics Education*, 12(9), 545-554.

[30] Viswanath, G. (2023). A Real-Time Case Scenario Based On URL Phishing Detection Through Login URLS. *Material science and technology*, 22(9), 103-108.

****