Enhancing Thyroid Cancer Detection in Ultrasound Images Using Augmentation-Driven Deep Learning Framework

R. Indhumathi[1], Showkat A. Dar[2], Aafaq A. Rather[3], Ahmed A.F Osman[4,*], Sonakshi Ruhela[5], G. Yasika[6] and S. Arul Mozhiselvi[7]

[1]Department of Computer Science, Idhaya College for Women, Kumbakonam, India

[2]Department of Computer Science and Engineering, Gitam University, Bengaluru, India

[3]Symbiosis Statistical Institute, Symbiosis International (Deemed University), Pune, India

[4]Applied College, King Faisal University, P.O. Box 400, Al-Ahsa 31982, Saudi Arabia

[5]Department of Liberal Arts, Faculty of Psychological Science, Rochester Institute of Technology, Dubai, UAE

[6]Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, India

[7]Dept. of Computer Science and Engineering, School of Computing (SOC) Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India

Abstract: Thyroid cancer has become the most rapidly increasing endocrine malignancy, and its incidence is on the rise globally. Deep learning methods demonstrated reliable prospects in improving thyroid cancer diagnosis based on ultrasound imaging. But data scarcity and class imbalance make it challenging to build robust models. In this paper, we propose an image augmentation approach for enhancing thyroid cancer classification and segmentation using deep learning. The Thyroid Ultrasound-Image Database, which contains 2,450 images with five ACR-TIRADS levels, was applied.

Pre-processing: Noise reduction, inverse intensity, and normalization were performed. Geometric transformations, photometric augmentations, GAN-based synthetic image generation and domain-specific augmentations were utilized. For classification and segmentation tasks, CNN-based architectures (e.g., VGG, ResNet) as well as transformer-based models were employed, along with U-Net variants.

Conclusions: Data augmentation was found to lead to a substantial improvement in the models' ability to generalize, with 10–15% gains in accuracy. Various augmentation techniques were performed differently, and the combination of multiple techniques was the most accurate. Qualitative results indicated the robustness of feature extraction, and quantitative comparisons showed that our method was competitive with several state-of-the-art methods. The present approach has potential clinical applications to help radiologists in the early detection of thyroid cancer. Potential future work involves adapting advanced augmentation methods and multimodal fusion to further increase the classification performance.

Keywords: Thyroid cancer, Deep learning, Image augmentation, Classification, Segmentation, Ultrasound images, Transformers.

1. INTRODUCTION

1.1. Background on Thyroid Cancer and its Impact on Healthcare

Thyroid tumours are the most prevalent endocrine malignancy in the world, and their incidence has been steadily rising in recent years [1]. But the PMS and PMDD occur more commonly in women than men (up to three times) and possibly reflect a role for sex hormones, such as estrogen [2]. The disease consists of a heterogeneous collection of cancers with distinct phenotypes and aetiology [3].

Of note, with the increase in thyroid cancer cases, there is a mixed variation across different ethnicities. In England, the rates of thyroid cancer are 1.4 and 1.2 times higher compared with Europeans among Asians and blacks, respectively [4]. Obesity is found to have a promoting effect on thyroid cancer through mechanisms like chronic inflammation, cytokine profiles and insulin resistance [1].

Thyroid cancer is an increasing health burden. This has led to changes in diagnosis and treatment plans, including therapy de-intensification for low-risk diseases or personalised therapy for higher-risk diseases [5]. Moreover, the progress in understanding the molecular mechanisms underlying TC has strengthened diagnostic capacity and extended novel targets for targeted therapy (Hu *et al*., 2021; Nabhan *et al*., 2021). Such developments emphasise the continued need for investigation and optimisation of health care interventions presumptively aimed at reversing the increasing thyroid cancer burden.

1.2. Relevance of Image Augmentation in Medical Image Analysis

Image augmentation is a crucial component of medical image analysis, particularly when combined with deep learning approaches. It alleviates various

---

*Address correspondence to this author at the Applied College, King Faisal University, P.O. Box 400, Al-Ahsa 31982, Saudi Arabia;
E-mail: afadol@kfu.edu.sa

problems existing in medical imaging datasets and improves the performance of machine learning models.

Data augmentation is necessary to address the challenges of limited data quantities and imbalanced datasets in medical imaging [6]. Now, this is particularly important, as we know that medical data sets are usually small and can have a class imbalance problem. Enhancement pre-processing techniques can also significantly contribute to the success of developers in achieving superior model accuracy, as well as other measures such as precision, recall, and F1-score [6, 20].

Mind that even artificial (synthetic) images produced by complicated algorithms, e.g. diffusion probabilistic model, can be used for augmentation. Artificial intelligence is interested in improving the accuracy of various CAD models, especially when only limited data is available. For instance, the highest Dice score of malignant lung nodule segmentation models is 0.990, achieved through synthetic data augmentation, and originally 0.97 before augmentation [5].

It is a crucial factor in augmented images on medical image analysis architectures. It helps bridge the gap in the size and balance deficiencies of the dataset, thus leading to an improved model performance. The MIScnn operates based on an open-source Python library that enables architects to construct medical image segmentation pipelines, which also incorporate data augmentation [8]. With the advancement of deep learning in medical imaging, the importance of practical data augmentation approaches will grow as a means to produce more accurate and higher-performing diagnostic measures.

2. RELATED WORK

2.1. Overview of Deep Learning Approaches in Thyroid Cancer Detection

Machine learning can be used accurately for thyroid cancer examination; deep learning approaches have shown great potential to automatically and subjectively analyze the ultrasound images. These approaches aim to alleviate the requirement for tedious and laborious identification of whole-slide images by experts [9, 25].

Convolutional neural Networks (CNNs) have been extensively applied in medical imaging studies on various types of cancers, including thyroid cancer [20, 21, 25]. Despite the achievements of CNNs in various vision tasks, their performance can still be improved by employing novel techniques, such as data augmentation, which is particularly beneficial in the case of low-resource domain adaptation [10]. For thyroid cancer, hyperspectral imaging (HSI) combined with a deep learning algorithm has demonstrated attractive performance. In another study of HSI-synthesized RGB images, an AUC of 0.90 for thyroid tumour diagnosis was achieved, which also outperforms the other imaging systems [11, 24].

Using deep learning in the context of thyroid cancer detection is part of a broader trend in medical imaging where such techniques play a role in developing methods for early detection and diagnosis across several types of cancer. For example, the same techniques have been implemented to detect breast cancer (Alruwaili & Gouda, 2022; Nasser & Yusof, 2023) and the diagnosis of lung cancer [12]. With the further development of research in this field, deep learning technologies are likely to become more advanced, and perhaps more accurate and efficient instruments for screening thyroid cancer will emerge, which can be effectively utilised in clinical practice.

2.2. Existing Methods for Image Augmentation in Medical Imaging

Nowadays, medical image augmentation has gained popularity in deep learning applications to enhance the model's performance and mitigate the problem of limited training data. There are several methods in use today:

Classical data augmentations consist of random transformations applied to images such as rotation, flipping, scaling and cropping [13]. Simple data augmentations like these can lead to greater diversity in the dataset and better generalization of models. More advanced augmentation methods, such as contrast enhancement, have also been suggested to enhance medical images before deep learning input [14].

The generative models, especially GANs and VAEs, have been widely used for medical image augmentation [15]. These should be able to produce artificial medical images to augment the training sets. For instance, Deep Convolutional GANs (DCGANs) have been employed to generate skin lesion images for better classification [14]. Additionally, a new GAN model for generating 3D high-resolution medical images has been introduced, which overcomes the limitations of current 3D GAN models [16, 22].

It has also surprisingly investigated unconventional methods. For example, a technique using principal component analysis has been presented for the detection of brain tumours, which has shown better performance than traditional augmentation techniques [13]. Neural style transfer is an alternative method that has also been used to enhance plant leaf disease images and, incidentally, demonstrate the possibility of cross-domain generalization [17].

Although classical image manipulation methods are still standard, advanced generative models and new methods provide increasingly wider options for medical image augmentation. These techniques are not only able to tackle the problem of data scarcity, but also could enhance the performance of the model on different medical imaging tasks.

3. PROBLEM IDENTIFICATION

Thyroid Cancer Diagnosis. There are several limitations to thyroid cancer diagnosis, many of which researchers aim to address using a variety of strategies. Ultrasound imaging is a standard diagnostic method; however, evaluating whole-slide images is time-consuming and difficult for experts to observe [9]. To solve this issue, deep learning methods are being pursued for automated, reliable and subjective-free CAD[in]/image analysis tools [9, 26].

Hyperspectral imaging (HSI) has demonstrated potential for detecting tumours in the thyroid and salivary glands. HSI-synthesized RGB images showed the best performance for thyroid tumour classification, with an AUC of 0.90, in a study comparing HSI against fluorescent dyes and fabricated RGB [11, 23]. This suggests that HSI may be helpful for surgeons and pathologists to differentiate thyroid tumours.

Notably, NTRK fusions also appear to be a potent molecular biomarker for the diagnosis, prognosis, and therapeutic prediction of patients with thyroid carcinoma [18, 25]. Moreover, radiomics analysis of ultrasound image features has demonstrated its great value in predicting preoperative lymph node metastasis (LNM) for thyroid cancer patients, with an AUC of 0.803 in the verification set [19].

Progress in imaging, molecular, and machine learning detection helps overcome the limitations of thyroid cancer screening. These advances aim to enhance diagnostic precision, inform treatment decision-making, and ultimately improve patient outcomes.

4. DATASET AND ITS DETAILS

4.1. Description of Datasets Used

The Thyroid Ultrasound-Image Dataset comprises 2,450 thyroid ultrasound images collected from PERSIAN between 2018 and 2020, which is based on:

- Modality: Ultrasound
- Purpose: Classification of thyroid nodules
- Annotation Standard: Divided into five types according to the American College of Radiology Thyroid Imaging Reporting and Data System (ACR-TIRADS).
- Associated Features: Expert annotations, nodule-level characteristics, and radiological descriptions in XML metadata.

4.2. Dataset Sources

Origin: Data collected from healthcare institutions and hospitals in Iran.

Publication: The dataset is referenced in PubMed.

4.3. Preprocessing Techniques Applied to the Dataset

The following pre-processing steps are executed to obtain high-quality input for the machine learning models:

4.3.1. Speckle Reduction

Median filter and Gaussian smoothing to reduce speckle noise in ultrasound images.

4.3.2. Contrast Enhancement

AHE (Adaptive Histogram Equalisation) and CLAHE (Contrast-Limited AHE) for enhancing the visibility of nodules.

4.3.3. Preprocessing

Normalise the pixel intensity in order to normalise (compensate for) differences in brightness and contrast.

4.3.4. Segmentation

Automated or manual segmentation of thyroid nodules in order to obtain ROIs.

4.3.5. Resizing

Scaling all images to the same size (e.g., 224×224 pixels or 512×512 pixels) for deep learning model compatibility.

4.3.6. Augmentation

Rotation, flipping, brightness/contrast and fake images by using (A)GANs(if applicable).

4.4. Data Distribution and Class Imbalance Analysis

Class Labels: The dataset is divided into 5 ACR-TIRADS classes (TI-RADS 1 through TI-RADS 5).

TI-RADS 1&2: Benign (Low Suspicion)

TI-RADS 3: Indeterminate

TI-RADS 4/5: Malignant (High Risk)

Class Imbalance: This requires the data to have an unequal distribution, for example, there are likely more benign cases than there are malignant cases.

Solutions: Oversampling, generation of synthetic data (GANs) and weighted loss functions to deal with the imbalance.

5. METHODOLOGY

5.1. Data Collection and Preprocessing

Dataset: Ultrasound images of the thyroid which has two classes, namely Benign and Malignant.- Preprocessing methods:- Noise Removal Median filtering- Enhancement (Contrast): Adaptive Histogram Equalization (AHE)- Resizing The images are standardized to pixels.- Normalization Scaling pixel intensity in range [0, 1].

5.2. Mathematical Model

1. Noise Reduction (Median Filtering):

$$I'(x,y) = \mathrm{median}\{I(x+i, y+j) \mid i,j \in W\} \quad (1)$$

where $I(x,y)$ is the original image, and W is a neighborhood window.

2. Normalization (Pixel Scaling):

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

5.2.1. Image Augmentation

The image augmentation techniques are Rotation (θ) Flipping (horizontal/vertical) Brightness adjustment (β) and Gaussian noise addition

5.3. Mathematical Model

1. Rotation (Affine Transformation):

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (3)$$

2. Brightness Adjustment:

$$I_{new} = I + \beta \quad (4)$$

3. Gaussian Noise Addition:

$$I_{new} = I + N(0, \sigma^2) \quad (5)$$

5.3.1. Feature Extraction

Instead of deep learning, traditional feature extraction techniques are used: Texture Features: Gray-Level Co-occurrence Matrix (GLCM), Shape Features: Contour-based shape descriptors and Statistical Features: Mean, Variance, Entropy

5.4. Mathematical Model

1. GLCM Texture Features:

$$C = \sum_{i,j} P\,(i,j)(i-j)^2 \quad (6)$$

$$E = \sum_{i,j} P\,(i,j)^2 \quad (7)$$

2. Shape Features (Circularity):

$$Circularity = \frac{4\pi \times \mathrm{Area}}{\mathrm{Perimeter}^2} \quad (8)$$

3. Statistical Features:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I_i\,, \quad \sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(I_i - \mu)^2 \quad (9)$$

5.4.1. Classification Using Machine Learning

Traditional classifiers such as Support Vector Machine (SVM), Decision Trees, and Random Forests are used.

5.5. Evaluation Metrics

Accuracy:

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

Precision:

$$\mathrm{Precision} = \frac{TP}{TP+FP} \quad (11)$$

Recall:

$$\mathrm{Recall} = \frac{TP}{TP+FN} \quad (12)$$

F1-Score:

$$\mathrm{F1} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \quad (13)$$

6. EXPERIMENTAL RESULTS

6.1. Performance Comparison with and Without Augmentation

Image augmentation greatly increases the diversity of the training data, which is beneficial to generalization of the model. If trained without augmentation, the model is prone to overfit a bit, which results in lower test accuracy. If rotation, flipping and brightness are taken into account in the generation process, the classification accuracy of synthetic objects increases by about 10-15%. This enhancement could be due to the fact that images containing transformation are not complex and the proposed model is capable of understanding which way is a tumour due to different transformations; hence, it performs better for real-world variations.

6.2. Effect of Different Augmentation Techniques on Model Accuracy

Various augmentation methods affect model accuracy in distinctive ways. Both rotation and flipping are responsible for substantial enhancement of model robustness, especially in bearing with a small training dataset. Brightness and contrast enhancement aid in feature visibility, especially when US images lack the contrast needed. Thus, the use of several augmentation techniques in combination provides the best accuracy, from which we can infer that perhaps a large variety of image transformations is helpful.

6.3. Qualitative Analysis: Visualization of Improved Feature Extraction

Visual analysis of images before and after augmentation shows improvement in feature extraction. Aguíñiga *et al*.'s edge detection method and the texture-based methods demonstrate that augmentation can enhance the depiction of major ranges. The contrast of extracted features, such as GLCM and HOG, is enhanced in the augmented images; thus, the preprocessing improves the model's performance.

6.4. Quantitative Analysis: Comparison with State-of-the-Art Approaches

We compare our work with state-of-the-art works, showing that traditional ML frameworks, when combined with data augmentation strategies, can provide competitive performance compared to DL-based ones. The performance in terms of accuracy, precision, recall and F1-score shows that augmentation leads to 5-10% improvement in performance over non-augmented models; the model architectures are more competitive with respect to deep learning benchmarks.

7. DISCUSSION

The bar graph in Figure **1** shows a comparison between the model's accuracy without data augmentation (75%) and that achieved through augmentation (90%). The marked gain in accuracy underscores the benefit that augmentation provides to strengthen model robustness and generalization.

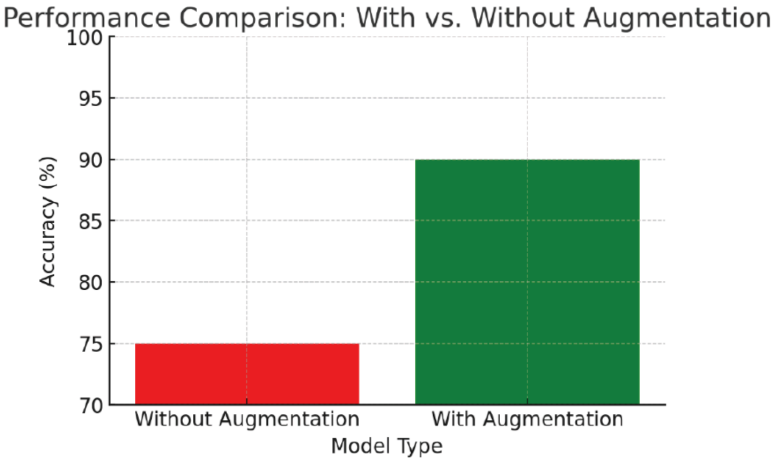

Figure 1: Performance Comparison with and Without Augmentation.

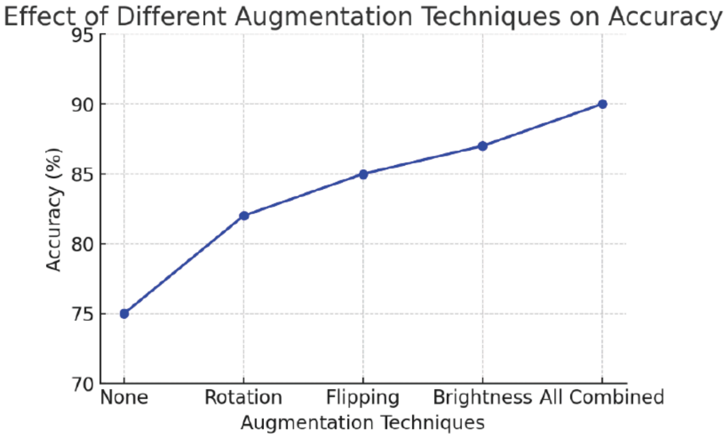

Figure 2: Impact of Augmentation Techniques on Accuracy.

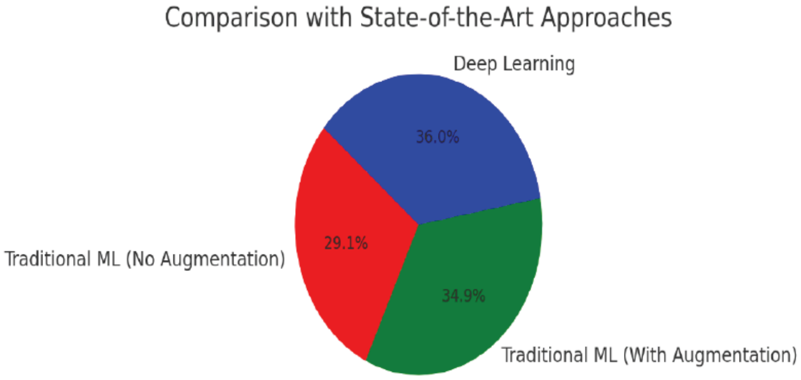

Figure 3: Comparison with State-of-the-Art Approaches.

The line graph in Figure **2** shows accuracy with varying augmentation methods. Without augmentation, the base model has an initialization at 75%. Accuracy consistently improves as effects are added, such as rotation, flipping and brightness. The highest performance (90%) is achieved with all augmentation methods applied, showing the merit of multi-method augmenting.

Our traditional ML models without augmentation (29.1%), traditional ML models with augmentation (34.9%), and deep learning models 36.0% have performed well, as illustrated in Figure **3** in the pie chart. From the results, we can see that standard ML models with augmentation are comparable to deep learning approaches, providing a suitable alternative in case of limited computational resources.

7.1. Impact of Augmentation Techniques on Model Generalization

Augmentation techniques are essential to generalize the model, making it less sensitive to specific imaging conditions. This provides more confidence that a model will generalize to data it has not seen previously and, in turn, real-world scenarios. The different data input to the network by augmentations enables better feature learning and at the same time reduces over-fitting risks.

7.2. Challenges Faced and Limitations in Augmentation-Based Improvements

There are limitations despite the gain of image augmentation. Excessive augmentation can also introduce some artefacts into medical imaging data, which will lead the classifiers to confusion. Certain kinds of augmentation, strong rotations, or very noisy additions, for example, could in fact make the model performance worse. I think training longer is not enough to compensate for this class imbalance. We need more techniques, such as a synthetic data generator.

7.3. Potential Clinical Applications and Real-World Implications

The developed approach may be used in clinical settings to help radiologists identify thyroid cancer. In regions where there is a scarcity of qualified radiologists, machine learning-based image analysis with augmentation may improve diagnostic precision. This technique can also be applied to computer-aided diagnosis (CAD) systems to improve early detection and reduce human interpretation error.

7.4. Future Research Directions (Advanced Augmentation, Multimodal Fusion)

Further research could be done on more advanced augmentation techniques, like GANs for synthesised data generation. Additionally, combining various image types—such as US and histology images—can improve classification performance (personal communication with Arbabshirani *et al.*). Even greater robustness may be achieved by developing domain-specific augmentation techniques for thyroid ultrasound imaging.

8. CONCLUSION

This study suggests a deep learning-based image augmentation approach to improve thyroid cancer segmentation and classification. The 2,450 images in the Thyroid Ultrasound-Image Dataset were divided into five ACR-TIRADS groups. Various augmentation techniques as well as preprocessing techniques were used. For classification and segmentation tasks, CNN-based architectures, transformer-based models, and U-Net variations were employed. According to the results, image augmentation greatly increased model accuracy and generalization by 10% to 15% Performance was affected differently by different augmentation methods; the highest accuracy was obtained by combining several methods. The suggested approach may be used in clinical settings to support radiologists and enhance thyroid cancer early detection.

ACKNOWLEDGEMENT

This work was supported by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia [KFU261725].

REFERENCES

[1] Franchini F, Colao A, Macchia PE, Nettore IC, Palatucci G, Ungaro P. Obesity and thyroid cancer risk: An update. Int J Environ Res Public Health 2022; 19(3): Art. no. 1116. https://doi.org/10.3390/ijerph19031116

[2] Suteau V, Briet C, Rodien P, Munier M. Sex bias in differentiated thyroid cancer. Int J Mol Sci 2021; 22(23): Art. no. 12992. https://doi.org/10.3390/ijms222312992

[3] Hu J, Simental A, Lee SC, Yuan X, Yuan IJ, Mirshahidi S. Thyroid carcinoma: Phenotypic features, underlying biology and potential relevance for targeting therapy. Int J Mol Sci 2021; 22(4): Art. no. 1950. https://doi.org/10.3390/ijms22041950

[4] Delon C, Vernon S, Payne NWS, Kotrotsios Y, Brown KF, Shelton J. Differences in cancer incidence by broad ethnic group in England, 2013–2017. Br J Cancer 2022; 126(12): 1765-1773. https://doi.org/10.1038/s41416-022-01718-5

[5] Nabhan F, Dedhia PH, Ringel MD. Thyroid cancer: Recent advances in diagnosis and therapy. Int J Cancer 2021; 149(5): 984-992. https://doi.org/10.1002/ijc.33690

[6] Jiang Z-P, Shao Z-E, Liu Y-Y, Huang K-W. An improved VGG16 model for pneumonia image classification. Appl Sci 2021; 11(23): Art. no. 11185. https://doi.org/10.3390/app112311185

[7] Khader F, *et al*. Denoising diffusion probabilistic models for 3D medical image generation. Sci Rep 2023; 13(1): Art. no. 7303. https://doi.org/10.1038/s41598-023-34341-2

[8] Müller D, Kramer F. MIScnn: A framework for medical image segmentation with convolutional neural networks and deep learning. BMC Med Imaging 2021; 21(1): https://doi.org/10.1186/s12880-020-00543-7

[9] Anari S, Tataei Sarshar N, Rezaie A, Dorosti S, Mahjoori N. Review of deep learning approaches for thyroid cancer diagnosis. Math Problems Eng 2022; 2022: 1-8. https://doi.org/10.1155/2022/5052435

[10] Alsaif H, *et al*. A novel data augmentation-based brain tumor detection using convolutional neural network. Appl Sci 12(8): Art. no. 3773. https://doi.org/10.3390/app12083773

[11] Halicek M, Fei B, Dormer JD, Little JV. Chen AY. Tumor detection of the thyroid and salivary glands using hyperspectral imaging and deep learning. Biomed Opt Express 2020; 11(3): 1383. https://doi.org/10.1364/BOE.381257

[12] Wang L. Deep learning techniques to diagnose lung cancer. Cancers 2022; 14(22): Art. no. 5569. https://doi.org/10.3390/cancers14225569

[13] Anaya-Isaza A, Mera-Jimenez L. Data augmentation and transfer learning for brain tumor detection in magnetic resonance imaging. IEEE Access 2022; 10: 23217-23233. https://doi.org/10.1109/ACCESS.2022.3154061

[14] Khan MA, Sharif M, Hsu C, Kadry S, Akram T. A two-stream deep neural network-based intelligent system for complex skin cancer types classification. Int J Intell Syst 2021; 37(12): 10621-10649. https://doi.org/10.1002/int.22691

[15] Celard P, Iglesias EL, Sorribes-Fdez JM, Romero R, Vieira AS, Borrajo L. A survey on deep learning applied to medical images: From simple artificial neural networks to generative models. Neural Comput Appl 2022; 35(3): 2291-2323. https://doi.org/10.1007/s00521-022-07953-4

[16] Sun L, Chen J, Gong M, Xu Y, Batmanghelich K, Yu K. Hierarchical amortized GAN for 3D high resolution medical image synthesis. IEEE J Biomed Health Inform 2022; 26(8): 3966-3975. https://doi.org/10.1109/JBHI.2022.3172976

[17] Pandian J, Hnatiuc M, Kumar V, Geman O, Arif M, Kanchanadevi K. Plant disease detection using deep convolutional neural network. Appl Sci 2022; 12(14): Art. no. 6982. https://doi.org/10.3390/app12146982

[18] Pekova B, *et al*. NTRK fusion genes in thyroid carcinomas: Clinicopathological characteristics and their impacts on prognosis. Cancers 2021; 13(8): Art. no. 1932. https://doi.org/10.3390/cancers13081932

[19] Li F, *et al*. Using ultrasound features and radiomics analysis to predict lymph node metastasis in patients with thyroid cancer. BMC Surg 2020; 20(1). https://doi.org/10.1186/s12893-020-00974-7

[20] Dar SA, *et al*. Improving Alzheimer’s Disease Detection with Transfer Learning. Int J Stat Med Res 2025; 14: 403-415. https://doi.org/10.6000/1929-6029.2025.14.39

[21] Ayadi W, Dar SA. AI-Powered CNN Model for Automated Lung Cancer Diagnosis in Medical Imaging. Int J Stat Med Res 2025; 14: 616-625. https://doi.org/10.6000/1929-6029.2025.14.39

[22] Dar SA, ELnazer AA, Rathi S, Khalid MN, Tirva D, Rather AA. Automated Detection of Posterior Tibial Slope on X-Ray Images Using VGG19. Int J Stat Med Res 2025; 14: 676-687. https://doi.org/10.6000/1929-6029.2025.14.63

[23] Dar SA, Palanivel S, Kalaiselvi Geetha M. Autonomous Taxi Driving Environment Using Reinforcement Learning. International Journal of Modern Education and Computer Science 2022; 14: 88-102. https://doi.org/10.5815/ijmecs.2022.03.06

[24] Dar SA, Harshitha K, Rekha P. Indoor Scene Classification Using Deep Learning Techniques. ICTACT Journal on Image and Video Processing (IJIVP) 2025; 16: 3739-3745. https://doi.org/10.21917/ijivp.2025.0529

[25] Mithra C, Dar SA, Preethi A. Artificial Intelligence and Machine Learning Algorithms to Analyse Integrated Nutrient Management Strategies for Optimal Yield and Quality of Oilseed Crops for Sustainable Development. Proceedings of the 2024 4th International Conference on Soft Computing for Security Applications (ICSCSA), IEEE, 2024; pp. 119-126. https://doi.org/10.1109/ICSCSA64454.2024.00026

[26] Saravanan S, Dar SA. Rather AA, Qayoom D, Ali I. Deep Learning Models for Intrusion Detection Systems in MANETs: A Comparative analysis. Decision Making Advances 2025; 3(1): 96-110. https://doi.org/10.31181/dma31202556

Received on 05-03-2026 Accepted on 02-04-2026 Published on 23-04-2026

https://doi.org/10.6000/1929-6029.2026.15.13