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High Accuracy Ultrasound Image-Based Deep Learning for Ovarian Cyst Classification

Aditi Gupta[1*], Sudeep Varshney[2] and Hoor Fatima[3]
[1]Research Scholar, Department of Computer Science and Engineering, School of Engineering and Technology, Sharda University, Greater Noida, Uttar Pradesh, India
[2]Associate Professor, Department of Computer Science and Engineering, School of Engineering and Technology, Sharda University, Greater Noida, Uttar Pradesh, India
[3]Assistant Professor, School of Computer Science Engineering and Technology, Bennett University, Greater Noida, Uttar Pradesh, India
[*]Corresponding Author: gpaditi77@gmail.com

Abstract: Ovarian cysts present a significant health risk for women of all ages throughout the world. The identification and classification of ovarian cysts is one of the complicated medical tasks. Correct and precise identification of ovarian cysts can help patients for their speedy recovery and healthy well-being. Recently, Deep Learning models have become valuable tools for classification in medical imaging. This paper presents an improved Densely connected Network (DenseNet-169) to classify ovarian cysts with high efficacy. The effectiveness of the proposed model is assessed by evaluation indicators, such as accuracy, precision, f1-score and recall. DenseNet-169 has proved to be a better Deep Learning model for accurate and reliable categorization of ovarian cysts using ultrasound images with 100% as recall, 99.78% as accuracy, 99.58% as precision and 99.79% as F1-score. This paper marks a significant advancement in distinguishing cystic ovaries from normal ones and thereby, contributing to improved diagnostic capabilities in ovarian pathology.

Keywords: Deep learning, DenseNet-169, Ovarian cyst classification, Ultrasound images.

I. Introduction

Nowadays, a major concern affecting women globally is ovarian cysts. These fluid-filled vesicles form inside the ovary or on its surface cause several health problems to women [1]. The reason for the arousal of ovarian cysts may be due to hormone imbalances, diseases related to reproduction and genetic predispositions. In majority cases, ovarian cysts are harmless and diminishes on their own, but sometimes, they can cause severe pain, infertility, and in few instances, ovarian cancer [2]. Thus, detection and classification of ovarian cysts is essential at an initial stage for the patient in order to dispense correct and effective diagnosis.

Magnetic resonance imaging (MRI), computed tomography (CT) and ultrasound are the radiology techniques that aid medical practitioners to detect ovarian cysts. The most common radiology technique used is ultrasound as it is less expensive, radiation free and a non-surgical procedure. It helps to find out location, dimension, texture and structure of ovarian cysts [3]. But still, effectiveness of ultrasound relies on the expertise of radiologist. Unskilled radiologist may overlook minute indicators of presence of cysts in ovaries or mistakenly find normal formations in ovary as cysts. To avoid such situations, automatic diagnosis system may assist healthcare professionals in making clinical decisions accurately [4].

Deep learning (DL) is subtype of machine learning that is capable of providing accurate analysis on complex image data. The foremost aim of the paper is to enhance the prognosis and classification of ultrasound images either as cystic ovary or normal ovary using a proposed DL model and hence, provide a support tool for healthcare professionals in their clinical decision process and patient care.

II. Related Work

There are several DL models implemented for ovarian cyst classification in recent years. Raja and Suresh designed a 2D Convolutional Neural Network model (CNN) on 240 ultrasound images to differentiate ovarian cysts like, follicular cyst, endometriosis, cystadenoma cyst, cancer cysts, polycystic ovaries, dermoid cysts, pelvic infections from normal ovaries [5]. In this implementation, for training 160 images are employed and for testing 80 images are employed. The images are of 128 × 128 size and are collected from various public sectors. The model achieves 99.37% as accuracy in detection and classification of ovarian cysts.

Few researchers used DenseNet-161, ResNet-152 and EfficientNet-B7 to classify ovarian endometriosis cyst (OEC) from tubal-ovarian abscess (TOA) on 202 ultrasound images [6]. These models are checked against evaluation metrics like, accuracy, sensitivity, and specificity for their performance. The outcomes of the models are compared with results of carbohydrate antigen 125 (CA125) and three ultrasound radiologists. ResNet-152 has emerged as a better CNN model to distinguish OEC from TOA with 0.986 as the area under receiver operating characteristic, 96.8% as accuracy, 90% as recall and 100% as specificity.

A lightweight Deep Learning model called Ocys-Net is fabricated to find out ovarian abnormalities [7]. It utilizes efficient channel attention module for local cross-channel interaction by removing shortcomings of dimensionality reduction. This lightweight model discerns textural features from ultrasound images of 224 × 224 size. This model uses improved ShuffleNet V2 on 750 ultrasound images that has 250 images of normal ovary, cystic ovary and impure ovarian cyst, respectively. The Ocys-Net gives results with an accuracy of 95.93%.

Another model OCD-FCNN (Ovarian Cysts Detection and Classification using Fuzzy Convolutional Neural Network) classifies ovarian cysts from 440 ultrasound images procured from SRM medical science hospital located at Chennai, TN, India[8]. The model implements a CNN to discover patterns from images and forward these patterns to Fuzzy Convolutional Neural Network (FCNN) which is rule based classifier. The FCNN involves fuzzy logic to handle uncertainty and ambiguity in classifying ovarian cysts. Training and testing are accomplished using 320 and 120 images, respectively. These images contain normal ovaries and cysts like, cystadenomas, follicular cysts, dermoid cysts, endometriosis cysts, pelvic infections, polycystic ovaries and cancer cysts. The model achieves 98.37% accuracy in the classification of ovarian cysts.

Narmatha and other researchers proposed a Harris Hawk Optimization (HHO) with deep Q network to distinguish ovarian cysts like haemorrhagic cyst, follicular cyst, dermoid cyst, endometriosis cyst, teratoma, polycystic ovary and corpus luteum cyst [9]. In this model, patterns found in ultrasound images are discovered by CNN using HHO and Deep Q network. This research is conducted on 478 images collected from Royal Victoria Hospital in Montreal, Canada. The model achieved accuracy of 97%, F1-score of 96.5%, precision of 96% and recall of 96%. The obtained results exceed the results of CNN, artificial neural networks and AlexNet models.

The researchers suggested a DL model with Support Vector Machine (SVM) to classify 374 ultrasound images of ovarian cysts [10]. It segregates five categories of cysts present in ovary – dermoid, endometriosis, polycystic ovaries, haemorrhagic and malignant cysts. 351 and 23 ultrasound images are used for training and testing purposes, respectively. The model performs better from previous models by gaining accuracy of 97.3%.

Another study developed a neural network-based technique to detect and segment cysts in ovaries from 80 ultrasound images [11]. The pre-processing procedures applied on images are resizing, median filtering and binarization to improve the quality of images. Then, region of interest is filtered out using bounding box technique of image segmentation. Finally, CNN is implemented to extract patterns and classify ovarian cysts like endometriosis cysts, dermoid cysts and haemorrhagic cysts. This CNN-based method gives accuracy of 94%.

A fine-tuned VGG-16 DL model is designed to classify ovarian cysts from 240 ultrasound images [12]. Training and testing are performed using 160 and 80 images, respectively. The fine-tuning is achieved by altering final 4 layers. The VGG-16 model proposed in the research gives accuracy of 92.11% for classification of ovarian cysts from ultrasound images.

To enhance accuracy in classifying ovarian cysts, this paper proposes a DL model with well-organized architecture to classify ovarian cysts from normal ovaries using ultrasound images and thereby, acts as a tool to aid healthcare professionals in providing quick, precise and reliable diagnosis and treatment plan of patients.

III. Methodology

The methodology of ovarian cyst classification begins with collection of ultrasound images of ovaries. After collection, the images are pre-processed to improve their quality. Once pre-processing is completed, Deep Learning models are used to distinguish between normal ovaries and cystic ovaries. Fig. 1 demonstrates the methodology utilized in this research.

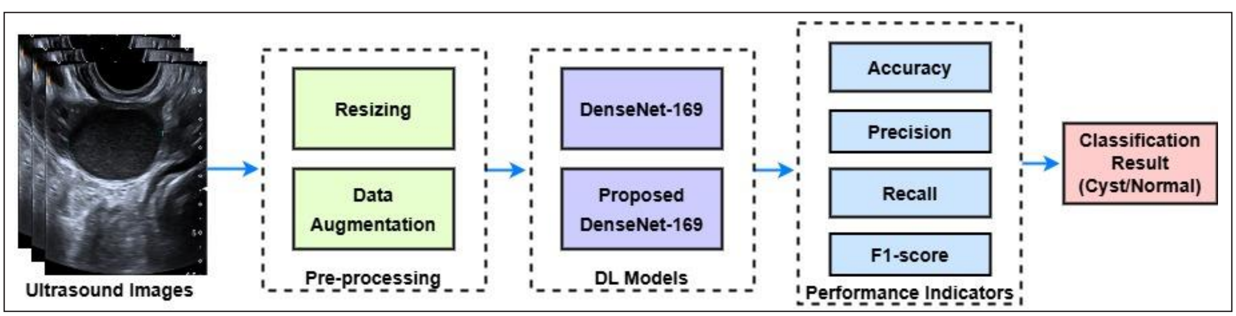

Fig. 1: Methodology

A. Acquisition of Data

The ultrasound data is obtained from “Skop” diagnostic centre, Agra, India. This dataset encompasses abdominal and transvaginal ultrasound images of normal ovaries and five types of ovarian cysts - haemorrhagic cyst, corpus luteum cyst, follicular cyst, dermoid cyst and chocolate cyst or endometriosis. The images are collected from ultrasound machine, Xario 100 that has 11 MHz probe frequency. To protect patient's information, all the details of patient linked to ultrasound images are removed before dataset is provided. Fig. 2 shows a sample of ultrasound dataset.

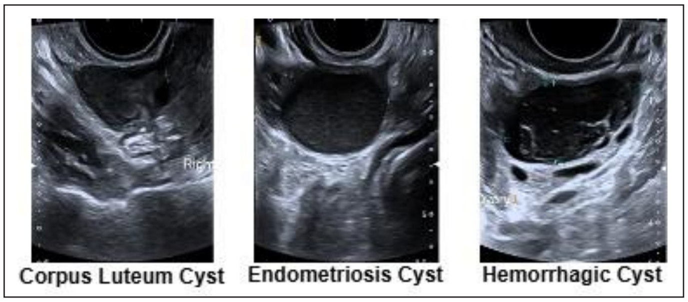

Fig. 2: Sample Ultrasound Dataset

B. Pre-Processing of Data

Data augmentation is a popular method to handle datasets of small size. It introduces variation in the dataset by adding new data [13]. This addition of new data is achieved through transformations like rotation, horizontal flip, vertical flip and shear on existing dataset [14]. These augmented images are resized to 224 × 224 as DenseNet-169 requires input image of 224 × 224 dimensions.

C. Proposed Deep Learning Model

Convolutional Neural Networks (CNN) are specialized DL models capable of finding out hierarchical representations in the images and manage voluminous image data [15]. Because of its inherent characteristics, CNN are popularly acceptable in various image applications like recognition, detection, classification and segmentation [16-21].

The experiment is performed using Intel(R) Core (TM) i5-5300U CPU and NVIDIA Tesla V100 GPU using version 3.10 of Python with Keras library. The dataset split ratio for training and testing images used is 75%, 25%, respectively. For the implementation, Adam (Adaptive Moment Estimation) optimization algorithm is used with 0.01 as rate of learning. Batch size, drop out and epochs are set to 32, 0.2 and 300, respectively. The sigmoid activation function is applied to the last neuron with 0.5 as threshold value. In order to find out training loss, binary cross-entropy loss function is utilized. At each epoch, loss is checked on the validation set and the model having minimum validation loss is chosen to depict training trial. The final model is trained using refined hyperparameters for best performance.

The research uses DenseNet-169 that is pretrained on ImageNet database made up of more than 14 million images [22]. ImageNet database consists of natural images and so, the weights of model may not function properly on medical images. To handle such circumstance, the research uses transfer learning and the pre-trained weights are used to deduce patterns from ultrasound images. DenseNet-169 takes 224 × 224 sized images as input. The vanishing gradient problem is resolved by DenseNet-169 model with the notion in which every layer receives input from all previous layers. It uses 6, 12 and 32 layers in dense blocks with batch normalization, convolutional and average pooling layers. The activation function used in fully linked and convolutional layers is Rectified Linear Unit function (RELU). The proposed DenseNet-169 model uses a sequence of flatten layer, fully connected layers of 256, 128, 64, 32 and 16 nodes with interspersing dropout and batch normalization layers instead of classification layer on the similar grounds of the experiments performed by F. R. Eweje *et al.* [23]. The flatten layer converts multidimensional image data into one dimension while keeping intact the information needed to link with completely connected layers. Batch normalization layer is used to solve issues related to vanishing gradients and speeds up training. Finally, sigmoid activation function is utilized with single node to differentiate ovarian cysts from normal ovaries.

IV. Result and Discussion

A. Performance Indicators

To check the performance of proposed DenseNet-169, a confusion matrix is created using TP, TN, FP and FN as True Positive, True Negative, False Positive and False Negative, respectively and is shown in Table I. Using these values, performance indicators namely accuracy, F1-score, recall and precision are computed using mathematical formulas given in Table II to analyse the efficacy of algorithms [24].

Table I: Confusion Matrix

	Predicted Negative	*Predicted Positive*
Real Negative	T_N	F_P
Real Positive	F_N	T_P

Table II: Performance Indicators

Parameters	*Formula*
Accuracy	$\frac{T_N + T_P}{T_P + T_N + F_P + F_N}$
Recall	$\frac{T_P}{T_P + F_N}$
Precision	$\frac{T_P}{T_P + F_P}$
F1-score	$\frac{2 * Precision * Recall}{Precision + Recall}$

Receiver Operating Characteristic curve (ROC) is calculated by Area under the ROC curve (AUROC) to assess how well DL classifier is performing. It uses True Positive Rate (TPR) and False Positive Rate (FPR) on various thresholds. The formulas for TPR and FPR provided in equations (1) and (2), respectively.

$$TPR = \frac{T_P}{T_P + F_N} \tag{1}$$

$$FPR = \frac{F_P}{F_P + T_N} \tag{2}$$

AUROC describes potential of the DL classifier; a value closer to 1 depicts that the classifier is performing better in classification.

B. Result Analysis

This section evaluates the performance of proposed DenseNet-169 DL model on ultrasound images. The confusion matrix of the implementation is given in Fig. 3.

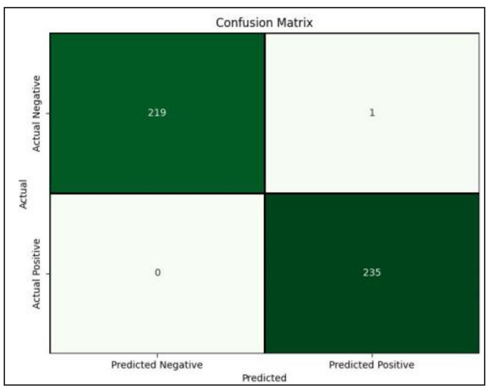

Fig. 3: Confusion Matrix of Proposed DenseNet-169

Utilizing TP, TN, FP and FN obtained from the confusion matrix, performance indicators are computed and displayed in Table III. The table specifies these indicators on both DenseNet-169 base model and proposed DenseNet-169 model. Comparing with base model, proposed DenseNet-169 has obtained better performance indicators, like accuracy 99.78%, recall 100%, f1-score 99.79% and precision of 99.58%. The results are highlighted in the table. The pictorial comparison of base model with proposed DenseNet-169 model is portrayed in Fig. 4.

Table III: Performance Indicators on Ovarian Cyst Dataset

Performance Indicators (%)	*DenseNet-169*	*Proposed DenseNet-169*
Accuracy	97.89	99.78
Recall	99.20	100
Precision	98.53	99.58
F1-score	97.91	99.79

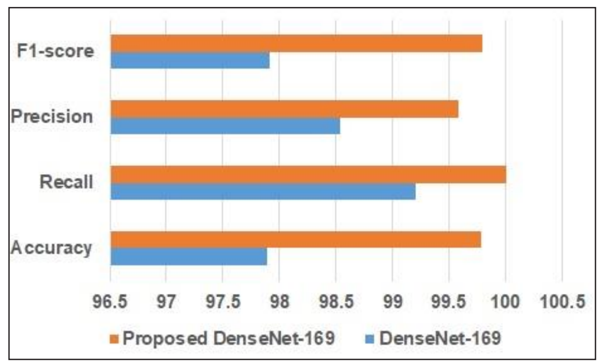

Fig. 4: Comparison of Performance Indicators of Base Model with Proposed DenseNet-169

Fig. 5 demonstrates training and validation - accuracy and loss curves for the proposed DenseNet-169 model. The figure shows that sometimes accuracy reached 100 percent.

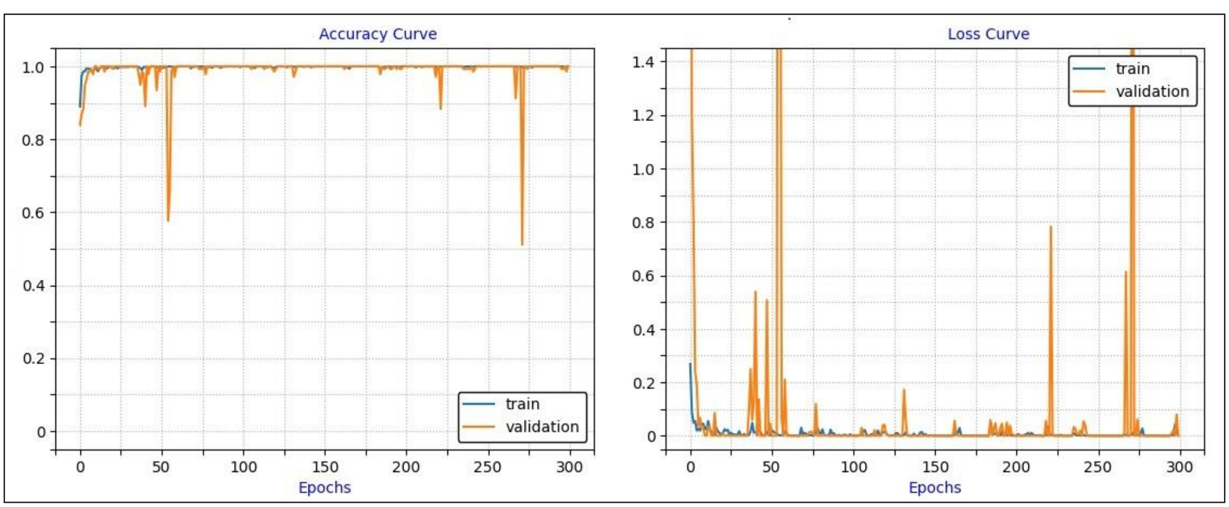

Fig. 5: Training and Validation - Accuracy and Loss Curves

The research additionally matches outcomes of proposed DenseNet-169 model proposed in this work with the latest ovarian cyst DL classification models implemented on the same pattern of training and testing dataset, 75%-25%, respectively. Table IV furnishes the details of the comparison. FCNN with 98.37% accuracy performs better than Improved ShuffleNet V2 (95.93%) and Deep Q Network with Harris Hawk Optimization (97%). The proposed DenseNet-169 has outshined other classifiers with 99.78% accuracy. Henceforth, proposed DenseNet-169 is a better tool of decision for healthcare providers in relation with ovarian cysts and can definitely help in forming quick and reliable treatment plans for patients. Fig. 6 depicts the accuracy comparison of ovarian cyst classifiers.

Table IV: Comparison between Proposed DenseNet-169 with Latest DL Classifiers for Ovarian Cyst Classification

References	*Year*	*Models*	*Accuracy (%)*
[7]	2023	Improved ShuffleNet V2	95.93
[8]	2023	Fuzzy Convolutional Neural Network (FCNN)	98.37
[9]	2023	Deep Q Network with Harris Hawk Optimization	97.0
Proposed	2024	Fine-tuned DenseNet-169	99.78

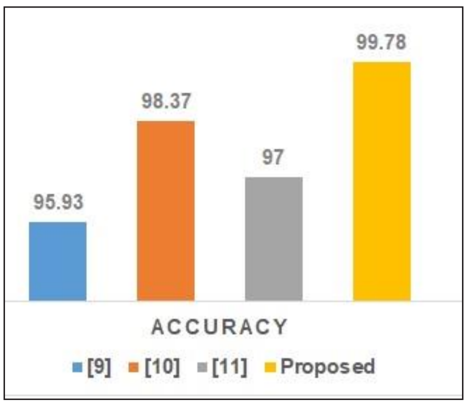

Fig. 6: Accuracy Result Comparison

Fig. 7 represents the comparison result of recall. The proposed classifier of this research gains 100% in recall and surpasses all other classifiers' recall outcomes.

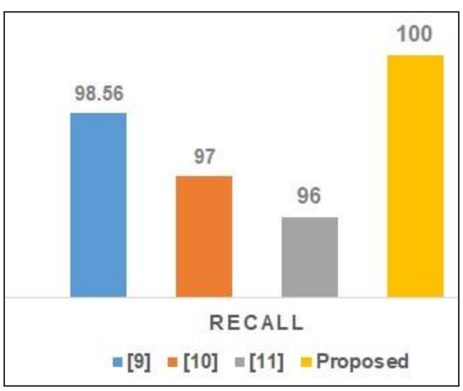

Fig. 7: Recall Result Comparison

The comparison results of precision of proposed DenseNet-169 with other classifiers is portrayed in Fig. 8. The proposed DenseNet-169 model obtains precision of 99.58% compared to lower values of precision of other models from latest ovarian cyst literature.

On similar grounds Fig. 9 delineates F1-score result comparison. The proposed classifier achieved 99.79% in F1-score which is far more than the other classifiers' F1-score outcomes.

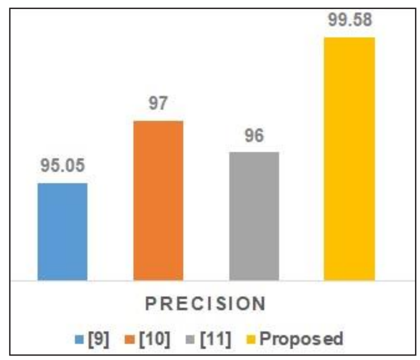

Fig. 8: Precision Result Comparison

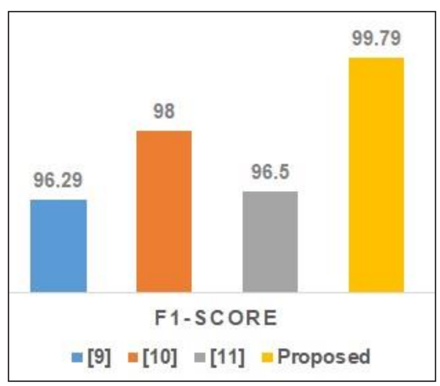

Fig. 9: F1-Score Result Comparison

V. Conclusion

The research work proposes an accurate, quick and reliable DL model for ovarian cyst classification with lowest pre-processing required for ultrasound images. The proposed model is analysed using number of performance indicators like recall, precision, F1-score and accuracy. It is noteworthy that the proposed DenseNet-169 model excels in each of the performance indicators having accuracy as 99.78%, precision as 99.58%, recall as 100% and F1-score as 99.79%. It even surpasses various ovarian cyst classification models mentioned in the recent literature. Henceforth, proposed DenseNet-169 is a pre-eminent classification model to discern ultrasound images having cysts from normal ovaries and assist radiologists and healthcare providers for a fast, reliable and precise evaluation of imaging tests towards the treatment plan of patients.

References

[1] A. M. Parekh, and N. B. Shah, "Classification of ovarian cyst using soft computing technique," in *8th International Conference on Computing, Communications and Networking Technologies (ICCCNT'2017)*, Sept. 2017, doi: https://doi.org/10.1109/ICCCNT.2017.8203965.

[2] S. Mobeen, and R. Apostol, "Ovarian cyst," *National Library of Medicine*, 2022. Accessed: Nov. 20, 2023. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK560541/

[3] A. Gupta, and H. Fatima, "A systematic review of machine learning for ovarian cyst detection using ultrasound images," in *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, May 2023, pp. 201-206. doi: https://doi.org/10.1109/ICAAIC56838.2023.10140444.

[4] A. A. Alzubi, H. Al Moghrabi, M. A. Alzubi, S. A. Alzubi, and S. Arabia, "Methods for automatic cyst detection and classification in ultrasound images of the female genitalia using image processing," *Journal of Population Therapeutics and Clinical Pharmacology*, vol. 30, no. 6, pp. 297-305, 2023, doi: https://doi.org/10.47750/jptcp.2023.30.06.035.

[5] P. Raja, and P. Suresh, "Variety of ovarian cysts detection and classification using 2D convolutional neural network," *Multimedia Tools and Applications*, vol. 83, no. 16, pp. 49473-49491, 2024, doi: https://doi.org/10.1007/s11042-023-17439-7.

[6] P. Hu, Y. Gao, Y. Zhang, and K. Sun, "Ultrasound image-based deep learning to differentiate tubal-ovarian abscess from ovarian endometriosis cyst," *Frontiers in Physiology*, vol. 14, pp. 1-9, Feb. 2023, doi: https://doi.org/10.3389/fphys.2023.1101810.

[7] J. Fan, J. Liu, Q. Chen, W. Wang, and Y. Wu, "Accurate ovarian cyst classification with a lightweight deep learning model for ultrasound images," *IEEE Access*, vol. 11, pp. 110681-110691, Oct. 2023, doi: https://doi.org/10.1109/ACCESS.2023.3321408.

[8] T. N. Ravishankar, H. Makarand Jadhav, N. Satheesh Kumar, S. Ambala, and M. Pillai N, "A deep learning approach for ovarian cysts detection and classification (OCD-FCNN) using fuzzy convolutional neural network," *Measurement: Sensors*, vol. 27, p. 100797, Jun. 2023, doi: https://doi.org/10.1016/j.measen.2023.100797.

[9] C. Narmatha, P. Manimegalai, J. Krishnadass, P. Valsalan, S. Manimurugan, and M. Mustafa, "Ovarian cysts classification using novel deep reinforcement learning with Harris Hawks Optimization method," *Journal of Supercomputing*, vol. 79, no. 2, pp. 1374-1397, 2023, doi: https://doi.org/10.1007/s11227-022-04709-8.

[10] Y. Suganya, S. Ganesan, and P. Valarmathi, "Ultrasound ovary cyst image classification with deep learning neural network with support vector machine," *International Journal of Health Sciences*, vol. 6, no. S2, pp. 8811-8818, 2022, doi: https://doi.org/10.53730/ijhs.v6ns2.7304.

[11] R. Benazir Begam, V. Yogalakshmi, G. Saranya, D. Gururaj, S. Jagtap, and V. Ravanan, "Ovarian cyst detection using neural networks," *Proceedings of the International Conference on Electronics and Renewable Systems (ICEARS'2022)*, 2022, pp. 1827-1830, doi: https://doi.org/10.1109/ICEARS53579.2022.9752205.

[12] S. Srivastava, P. Kumar, V. Chaudhry, and A. Singh, "Detection of ovarian cyst in ultrasound images using fine-tuned VGG-16 deep learning network," *SN Computer Science*, vol. 1, no. 2, pp. 1-8, 2020, doi: https://doi.org/10.1007/s42979-020-0109-6.

[13] Y. Wang, G. Huang, S. Song, X. Pan, Y. Xia, and C. Wu, "Regularizing deep networks with semantic data augmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 7, pp. 3733-3748, 2022, doi: https://doi.org/10.1109/TPAMI.2021.3052951.

[14] B. Kayalibay, G. Jensen, and P. van der Smagt, "CNN-based segmentation of medical imaging data," 2017. [Online]. Available: http://arxiv.org/abs/1701.03056

[15] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60-88, Dec. 2017, doi: https://doi.org/10.1016/j.media.2017.07.005.

[16] S. E. Nassar, I. Yasser, H. M. Amer, and M. A. Mohamed, "A robust MRI-based brain tumor classification via a hybrid deep learning technique," *Journal of Supercomputing*, vol. 80, no. 2, pp. 2403-2427, 2024, doi: https://doi.org/10.1007/s11227-023-05549-w.

[17] A. Kodipalli, S. L. Fernandes, and S. Dasar, “An empirical evaluation of a novel ensemble deep neural network model and explainable AI for accurate segmentation and classification of ovarian tumors using CT images,” *Diagnostics*, vol. 14, no. 5, 2024, doi: https://doi.org/10.3390/diagnostics14050543.

[18] A. Kodipalli, S. L. Fernandes, V. Gururaj, S. Varada Rameshbabu, and S. Dasar, “Performance analysis of segmentation and classification of CT-scanned ovarian tumours using U-Net and deep convolutional neural networks,” *Diagnostics*, vol. 13, no. 13, 2023, doi: https://doi.org/10.3390/diagnostics13132282.

[19] R. V. Manjunath, A. Ghanshala, and K. Kwadiki, “Deep learning algorithm performance evaluation in detection and classification of liver disease using CT images,” *Multimedia Tools and Applications*, vol. 83, no. 1, pp. 2773-2790, 2024, doi: https://doi.org/10.1007/s11042-023-15627-z.

[20] C. Kamala, and J. M. Shivaram, “Segmentation of ovarian cyst using improved U-NET and hybrid deep learning model,” *Multimedia Tools and Applications,* vol. 83, pp. 42645-42679, 2024, doi: https://doi.org/10.1007/s11042-023-16998-z.

[21] A. Bruno, G. Ignesti, O. Salvetti, D. Moroni, and M. Martinelli, “Efficient lung ultrasound classification,” *Bioengineering*, vol. 10, no. 5, 2023, doi: https://doi.org/10.1007/s11042-023-16998-z.

[22] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition (CVPR’2017)*, Jan. 2017, pp. 2261-2269, doi: https://doi.org/10.1109/CVPR.2017.243.

[23] F. R. Eweje *et al.*, “Deep learning for classification of bone lesions on routine MRI,” *EBioMedicine*, vol. 68, 2021, doi: https://doi.org/10.1016/j.ebiom.2021.103402.

[24] M. Kalaiyarasi, R. Dhanasekar, S. Sakthiya Ram, and P. Vaishnavi, “Classification of Benign or Malignant tumor using machine learning,” *IOP Conference Series: Materials Science and Engineering*, vol. 995, no. 1, 2020, doi: https://doi.org/10.1088/1757-899X/995/1/012028.