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A Hybrid Deep Learning Framework for Accurate Polycystic Ovary Syndrome Detection Using Ultrasound Imaging

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ABSTRACT

Polycystic Ovarian Syndrome (PCOS) is a hormone-related health condition in women, commonly classified as an endocrine disorder. It is most prevalent during the childbearing years, typically between the ages of 15 and 44. PCOS leads to hormonal imbalances that cause irregular menstrual cycles, hair loss, and other symptoms, and it is associated with long-term health risks such as heart disease and diabetes. Recent advances in deep learning have shown promising results in accurately recognizing and differentiating ovarian cysts from other ovarian tumours. This study proposes a novel technique for PCOS symptom detection by analysing ovarian images through feature extraction, classification, and metaheuristic-based optimization. Ovarian images are first pre-processed for noise removal and smoothing, followed by feature extraction and classification using a Convolutional Wavelet Attention Neural Network with a Naïve Bayes Fuzzy Autoencoder (CWANN–NBFA). Optimization is then performed using the Metaheuristic Multilevel Hawks Algae Optimization (MMHAO) algorithm. Experimental evaluations were conducted on multiple ovarian image datasets. The proposed technique achieved an accuracy of over 98% across the PCOSUSG, KFHU, and MMOTU datasets, demonstrating its robustness and effectiveness in addressing the challenges of PCOS detection.

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1. INTRODUCTION

Ovaries are classified into three types based on their structural features: normal, cystic, and polycystic (Figure 1). In normal ovaries, cysts containing eggs form every month. Each cyst is filled with fluid and discharged during menstrual bleeding. Cysts that are not eliminated from the body persist in the ovarian tissue, resulting in polycystic ovaries. Although polycystic ovaries contain many follicles, they fail to mature, and ovulation does not occur. This is the primary distinction between polycystic and normal ovaries [1]. Polycystic ovarian syndrome (PCOS) is a hormonal condition characterized by a variety of symptoms. It affects approximately 20% of women of reproductive age. The Rotterdam criteria specify three diagnostic features of PCOS: chronic anovulation or menstrual irregularity, excessive androgenic hormones in women, and the presence of multiple follicles in ultrasound scans. Women exhibiting at least two of these features are considered to have PCOS [2]. A blood test is often performed to confirm the diagnosis of this condition. PCOS is associated with several health complications, including diabetes, insulin resistance, obesity, and cardiovascular disease. Therefore, early recognition and timely treatment are critical to preventing the development of secondary disorders. The primary indicators of PCOS include insulin resistance and elevated luteinizing hormone (LH) levels, which disrupt ovulation in women [3]. If left untreated, PCOS can lead to severe diabetes as well as cardiovascular complications. Ultrasonography (USG) is a medical imaging technique that employs high-frequency sound waves to produce two-dimensional black-and-white images. This imaging method is widely used for the diagnosis of PCOS. Beyond PCOS, ultrasound instruments are also used for the preliminary diagnosis of various medical conditions, including gallbladder disease, breast tumours, thyroid abnormalities, prostate issues, and gynaecological disorders. Deep learning, a rapidly evolving technology, has shown great potential in addressing challenges across various fields [4], [5]. In healthcare, it allows researchers and practitioners to uncover patterns in hidden data, thereby improving efficiency and outcomes. It also enhances diagnostic accuracy and treatment planning, enabling medical professionals to make better-informed decisions. Polycystic ovary syndrome (PCOS) is a medical condition for which no single definitive diagnostic test or universally effective treatment currently exists. Endocrine disorders causing infertility often lead to the development of ovarian cysts in women of reproductive age. The reproductive system plays a vital role in a woman's health. During reproduction, certain molecules released by the egg guide sperm toward its surface, facilitating fertilization. Fertilization typically occurs in the oviducts, though it can also happen in the uterus. PCOS remains a prominent topic in medical research. In the clinical evaluation of ovarian disorders, ultrasound has been the most widely used imaging modality [6]. Compared with computed tomography (CT) and magnetic resonance imaging (MRI), ultrasound offers several advantages—it is inexpensive, safe, easily accessible, and provides real-time imaging results [7]. With advances in imaging technologies, deep learning (DL) offers great potential for automated analysis, improving objectivity and diagnostic accuracy. Computer vision and image analysis, in particular, benefit significantly from DL applications. Automatic classification of PCOS using clinical data and ultrasound images can support early detection. Diagnosis of PCOS is based on multiple criteria and symptoms, often requiring reliable menstrual history and ultrasound examinations. However, due to its wide spectrum of symptoms and the absence of a single standardized diagnostic test, clinicians often rely on multiple clinical assessments and, at times, unnecessary radiological imaging. The complex pathophysiology of PCOS further complicates diagnosis, as some symptoms or test results may be inconsistent or irrelevant. Nevertheless, since PCOS directly leads to ovarian dysfunction, early identification and detection with minimal laboratory tests and imaging procedures remain essential [8], [9].

Figure 1. Illustration of normal, cystic, and polycystic ovaries showing typical follicular patterns.

Several digital image processing techniques are commonly employed in the construction of computer-aided PCOS follicle detection systems. For instance, H Chen et al. [10] suggested an automated technique to identify PCOS by separating the regions of follicles and cysts from ultrasound pictures. They applied many digital image processing techniques on 19 ultrasound pictures, including morphological erosion, K-means clustering, median filtering, histogram equalisation. In [11], they examined and contrasted two approaches for follicle detection utilizing image processing methods to diagnose PCOS: first involves binarization, morphological procedures, contrast modification, noise reduction, k-means clustering, hole filling, morphologic procedures. The analytical results were also compared to two performance indicators, false rejection rate (FRR) as well as false acceptance rate (FAR). Authors [12] presented an image processing-based approach to PCOS detection that uses active contour in conjunction with modified Otsu method to precisely quantify number of cysts in ultrasound ovary image. Two main components of their proposed method are follicle identification and image pre-processing. According to work [13], PCOS patients can be classified using scleral pictures and a deep learning architecture that combines ResNet 18, U-net, Multi Instance Learning method. Their dataset had 721 photos in all, 388 of which included PCOS patients. Their suggested method had an AUC of 98%, accuracy of 93% on average. Author [14] developed a method to identify PCOS in ultrasound images using image segmentation and convolutional neural networks (CNNs). Additionally, the pictures were categorised using the K-Nearest Neighbour technique. Using their own dataset, refined the 16 Layered VGG-16 model for PCOS classification from ultrasound pictures. The accuracy of their model was 92.11% used image binarization on B-mode ultrasound pictures. Author [15] used image binarization as an image preprocessing technique after converting ultrasonic images of ovarian cysts to greyscale images. After post-processing the images, the authors classified the cysts and extracted geometrical features by labelling and connecting the various components. They achieved 90% accuracy using SVM as their classifier. In order to categorise their PCOS dataset, work [16] assessed how well a variety of feature selection techniques and classifiers performed, in addition to their suggested hybrid feature selection and classification method. According to the experimental data, out of all the approaches examined, the hybrid strategy had the greatest classification accuracy. PCOS dataset from Obafemi Awolowo University was classified utilizing C4.5 Decision Tree, NB, MLP by Author [17]. Results demonstrated that C4.5 Decision Tree as well as MLP performed better than NB with an accuracy rate of 74.359. PCOS survey dataset was classed using three different classifiers in work. The results showed that NB outperformed the other two classifiers with an accuracy rate of 97.65%. The author [18] applied many classification techniques to diagnose PCOS early after using Principal Component Analysis (PCA) to identify the best aspects of their PCOS dataset, which was gathered from Thrissur infertility treatment facilities. RF performed better than the other classifiers, according to the results. Work [19] extracted the most important properties from the Kaggle PCOS dataset using a filter-based univariate feature selection technique. In order to classify PCOS using ten distinct features, they additionally used gradient boosting, RF, Logistic Regression (LR), Hybrid Random Forest and Logistic Regression (RFLR). According to results, RFLR performed better than other classifiers in terms of recall (90%) and classification accuracy (91.01%). In order to predict PCOS based on discovery of new genes, [20] used a variety of ML methods, including K-nearest neighbour (KNN), decision trees, SVM with different kernel functions. [21] developed an automated system that will serve as an aided tool for physician, saving a great deal of time during patient examinations, consequently, decreasing delay in diagnosing risk of PCOS by utilising metabolic and clinical factors in a feature vector. The system makes use of machine learning algorithms like Bayes and Logistic Regression (LR). [22], have conducted a thorough investigation on the illness and its three diagnostic criteria, providing us with information on anomalies related to insulin, gonadotropin, folliculogenesis in addition to PCOS. Machine learning models based on metabolic characteristic are proposed in work [23]. The author put out a model utilising the Statistical Package for the Social Sciences (SPSS) to illustrate the significance of metabolic traits. With an accuracy rating of 89.02%, RFC was shown to be the most pertinent and accurate technique for PCOS prediction.

These studies highlight the potential of integrating deep learning and machine learning for early detection and reliable diagnosis of PCOS. However, the complexity of PCOS symptoms and the heterogeneity of diagnostic data necessitate further advancements in developing robust and efficient diagnostic models that combine clinical data with imaging technologies. This paper aims to address these challenges by proposing a novel approach to PCOS diagnosis, leveraging the strengths of deep learning for autonomous analysis and improving diagnostic accuracy. Specifically, a robust system for detecting Polycystic Ovary Syndrome (PCOS) symptoms is proposed, integrating metaheuristic models and ensemble deep learning techniques. The system focuses on analysing key traits for PCOS prognosis and employs a deep learning method to extract essential features from ultrasound images, including shape and texture characteristics of ovarian cysts. The methodology incorporates pre-processing techniques to enhance ultrasound images, addressing challenges such as underexposure and noise. Adaptive Bilateral Filtering (ABF) improves image sharpness, while kernel adjustments ensure precise filtering. To further optimize classification performance, a Convolutional Wavelet Attention Neural Network (CWANN) is integrated with a Naïve Bayes Fuzzy Autoencoder (NBFA) model. This deep learning approach eliminates the need for manual feature extraction, enabling more accurate classification. The CWANN employs Gabor Wavelet filters and attention mechanisms to handle dimensionality and enhance feature extraction, ensuring high classification accuracy. The Metaheuristic Multilevel Hawks Algae Optimization (MMHAO) algorithm plays a key role in optimizing hyperparameters and structural configurations. By balancing exploration and exploitation, MMHAO refines model parameters, ensuring optimal classification accuracy for image-based PCOS detection. This hybrid optimization method is critical in handling high-dimensional datasets, ensuring the model's scalability and precision, which is validated against clinical standards for ovarian cyst diagnosis. Through this synergy, the proposed method achieves superior performance on multiple benchmark PCOS ultrasound datasets, demonstrating both robustness and clinical relevance. To the best of our knowledge, this is the first work to unify wavelet-based attention, fuzzy autoencoding, and bio-inspired metaheuristic optimization into a single framework for PCOS detection from ultrasound images.

2. RESEARCH METHOD

The proposed system for PCOS symptom detection integrates metaheuristic models and ensemble deep learning techniques to ensure accurate and reliable diagnosis. A simplified workflow of the system is illustrated in Figure 2, highlighting the major stages: data input, preprocessing, deep feature extraction, classification, optimization, and output. To capture both clinical and imaging features, the system identifies 19 traits that serve as the foundation for PCOS prognosis. The dataset is divided in a 70:30 ratio for training and testing. For robust classification, the framework automatically extracts shape and texture characteristics of non-pure ovarian cysts, normal pelvic cysts, and polycystic ovarian cysts. The detailed architecture of the proposed detection model is shown in Figure 3, where the Convolutional Wavelet Attention Neural Network (CWANN), Naïve Bayes Fuzzy Autoencoder (NBFA), and Metaheuristic Multilevel Hawks Algae Optimization (MMHAO) components are integrated for improved accuracy. The Gini coefficient is used to assess feature importance, and initial testing with traditional classifiers revealed that the Decision Tree achieved the most reliable baseline performance. Clinical validation is ensured through comparison with expert diagnoses ("gold standard"), with healthcare practitioners reviewing model outputs for reliability.

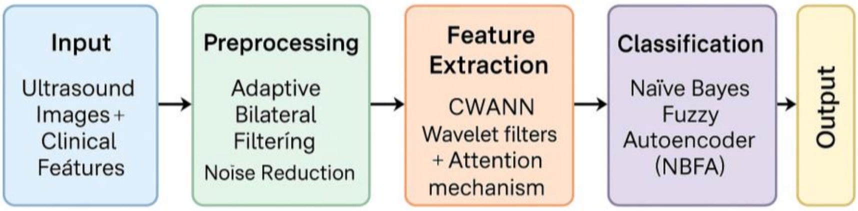


Figure 2. Simplified workflow of the proposed PCOS detection framework

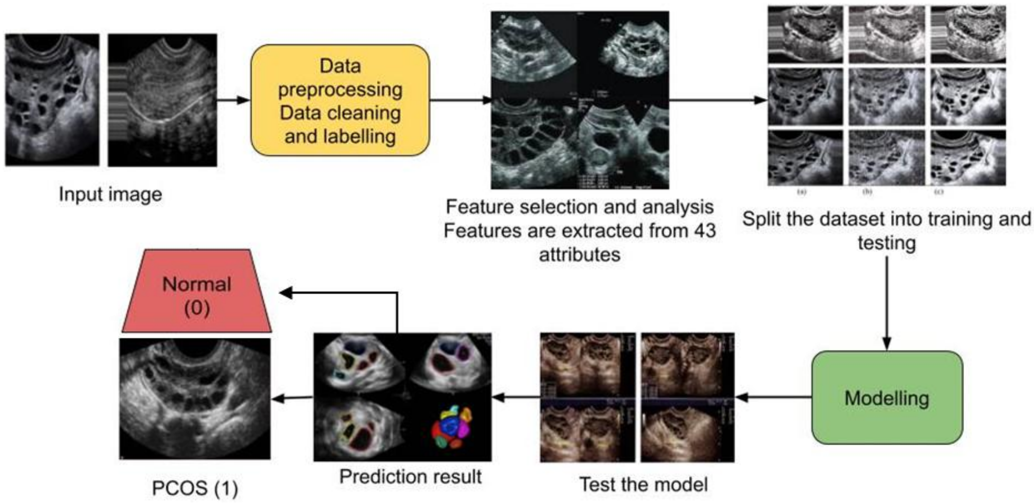


Figure 3. Detailed Architecture of the Proposed PCOS Detection Model

2.1 Preprocessing

Preprocessing addresses the challenge of distinguishing healthy and cystic regions in ultrasound (USG) images, especially when images are underexposed or noisy. Adaptive Bilateral Filtering (ABF) is employed to enhance image sharpness by selectively adjusting pixel intensities. Unlike the standard bilateral filter, which applies uniform smoothing, ABF modifies the kernel's centre and width dynamically, allowing sharper adjustments in critical regions.

Mathematical Formulation:

Let the input image be represented as f: I→R. The output image is computed as:

$$g(i) = \eta(i)^{-1} \sum_{j\in\Omega} \omega(j)\varphi i(f(i-j) - \theta(i)f(i-j)) \quad (1)$$

Where:

- Ω denotes the local window (neighbourhood) around pixel i.
- ω(j) is the spatial weight for pixel j within the window.
- ϕi(t) is the Gaussian range kernel at pixel i, defined as:

$$\varphi i(t) = \exp\left(-\frac{t^2}{2\sigma(i)^2}\right) \quad (2)$$

Where,

- σ(i) is the standard deviation of the Gaussian kernel, dynamically adjusted for each pixel to account for local intensity variations.
- θ(i) is an adaptive scaling factor to enhance contrast in underexposed regions.
- η(i) is the normalization factor ensuring that the weighted sum of intensities. This adaptive kernel ensures enhanced visibility of underexposed cystic regions.

2.2. Convolutional Wavelet Attention Neural Network with Naïve Bayes Fuzzy Autoencoder (CWANN–NBFA)

2.2.1 Convolutional Wavelet Attention Neural Network (CWANN).

The CWANN is specifically designed to extract discriminative features from ultrasound (USG) images by combining wavelet-based filters with attention mechanisms. The overall working principle of the CNN model is illustrated in Figure 4. Unlike conventional CNNs, which primarily capture local intensity variations, CWANN employs Gabor wavelet filters to model both *texture* and *shape* patterns of ovarian cysts across multiple scales and orientations [24], [25]. The detailed architecture of the CWANN, including the basic unit of the proposed network and the spatial down sampling module, is illustrated in Figure 5. These features are highly relevant for distinguishing polycystic ovaries from normal ones [26], as PCOS often presents with subtle morphological variations. The attention module further enhances this process by selectively emphasizing the most informative channels while suppressing redundant or noisy features. This is achieved through global average pooling (GAP), one-dimensional convolution, and sigmoid activation, enabling the network to capture inter-channel dependencies without dimensionality reduction errors. The result is a robust feature extractor that adapts to variations in cyst size, position, and imaging quality.

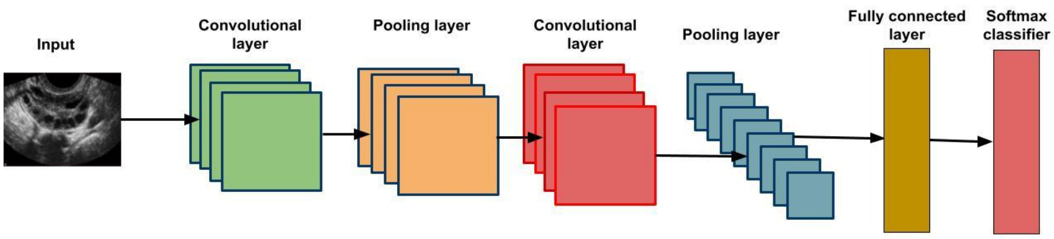


Figure 4. Working Principle of the CNN Model

2.2.2 Naïve Bayes Fuzzy Autoencoder (NBFA).

The NBFA integrates three concepts—autoencoding, fuzzy logic, and probabilistic classification—into a unified module. First, the autoencoder reduces high-dimensional CWANN feature maps into a compact latent representation through a bottleneck layer, ensuring efficient learning and generalization. Next, fuzzy logic models uncertainty inherent in ultrasound features, such as overlapping cyst boundaries or ambiguous tissue textures, by assigning partial membership values between 0 and 1 instead of binary class boundaries. Finally, the Naïve Bayes classifier operates on the latent fuzzy features to assign probabilistic class labels, leveraging prior and conditional probabilities to handle variability across patients. This hybrid mechanism enhances classification reliability in cases where deterministic approaches are prone to misclassification.

2.2.3 Integration of CWANN and NBFA.

Within the proposed framework, CWANN functions as the primary feature extractor, while NBFA performs uncertainty-aware dimensionality reduction and probabilistic classification. Together, they form a complementary pair—CWANN ensures that informative morphological and textural features are captured, and NBFA ensures that these features are robustly and reliably classified. Subsequently, the Metaheuristic Multilevel Hawks Algae Optimization (MMHAO) algorithm fine-tunes the hyperparameters of both modules, ensuring adaptability across datasets and maximizing diagnostic accuracy.

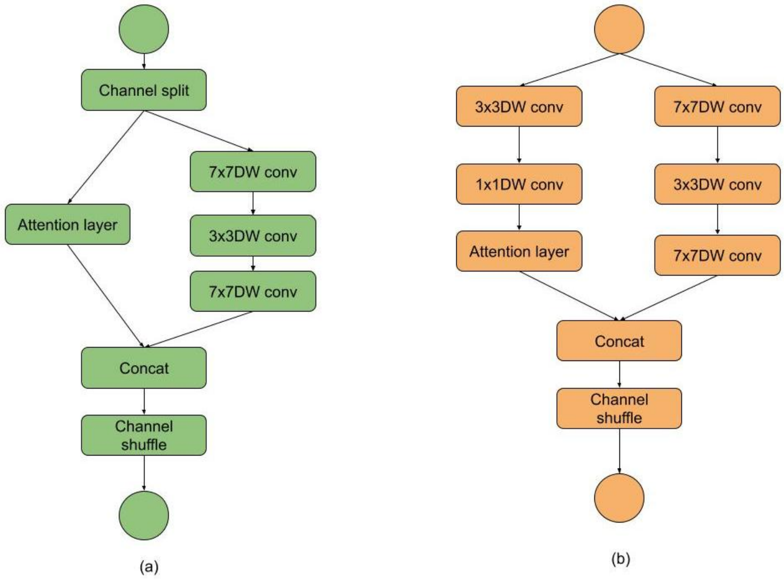


Figure 5 (a) Basic unit of proposed network. (b) Proposed unit for spatial down sampling

2.3. Metaheuristic Multilevel Hawks Algae Optimization (MMHAO)

The Metaheuristic Multilevel Hawks Algae Optimization (MMHAO) algorithm automates hyperparameter tuning and structural optimization to enhance system performance for PCOS detection. It balances exploration and exploitation to optimize classification accuracy, particularly in image-based tasks. Inspired by hawks' hunting strategies, MMHAO operates in two phases. In the exploration phase, hawks simulate dynamic movements to ensure broad and diverse coverage of the solution space. In the exploitation phase, they coordinate to refine promising solutions, mimicking collaborative decision-making to converge on optimal outcomes. To complement this, algae colonies adapt their size and movements based on proximity to optimal solutions. Larger colonies represent promising candidates, while smaller ones adapt or merge to improve efficiency. These movements are modelled in three dimensions, allowing adaptability to changing solution landscapes. By combining the hawks' strategies with algae's adaptability, MMHAO refines hyperparameters iteratively. This hybrid approach dynamically adjusts learning rates, kernel sizes, and latent dimensions, ensuring convergence toward optimal solutions. It effectively synergizes global exploration with local exploitation, achieving robust optimization for high-dimensional tasks. Within the proposed framework, MMHAO fine-tunes both the Convolutional Wavelet Attention Neural Network (CWANN) and the Naïve Bayes Fuzzy Autoencoder (NBFA). By optimizing critical parameters, MMHAO enhances the classification of ovarian cyst images, ensuring precise segmentation and reliable differentiation between normal and anomalous cases. Overall, this bio-inspired algorithm integrates adaptability and collaboration, providing precision, robustness, and scalability in PCOS detection. As such, MMHAO serves as a key component of the proposed methodology.

2.4 Dataset Description

To evaluate the proposed PCOS detection framework, three independent ultrasound datasets were employed: PCOSUSG, KFHU, and MMOTU. Together, these datasets ensure diversity by combining public, clinical, and cross-domain sources.

2.4.1 PCOSUSG Dataset (Kaggle)

The first dataset was obtained from Kaggle [27] and is referred to as the PCOSUSG dataset. It originally contained 1,924 training images and 1,932 test images; however, due to overlap between the two subsets, only the training set was used. After refinement, the dataset included 781 ultrasound images categorized as 'INFECTED' (cystic ovaries/PCOS cases) and 1,143 images categorized as 'NOT INFECTED' (healthy ovaries). These binary labels align with clinical practice, distinguishing individuals diagnosed with PCOS from those without the condition.

2.4.2 KFHU Dataset (Clinical Data)

The second dataset was collected from the Department of Radiology, King Fahad Hospital of University (KFHU), Khobar, Saudi Arabia [28]. It comprised 1,250 patient cases, of which 250 were diagnosed with polycystic ovaries and 1,000 were normal or exhibited other abnormalities. Four radiologists reviewed the ultrasound scans, and only images providing a clear view of the ovary were included in the study. Cases were categorized into polycystic ovary morphology (PCOM) and non-PCOM based on the diagnostic definition: multiple uniformly sized, peripherally arranged follicles smaller than one centimeter. This clinical validation ensures the dataset's reliability.

2.4.3 MMOTU Dataset (Cross-domain Ovarian Tumours)

To further assess generalizability, the MMOTU ultrasound dataset [29] was used. It consists of 1,639 ultrasound images from 294 patients, divided into two subsets: OTU-2D and OTU-CEUS. The dataset includes eight tumour classes, though distribution is unbalanced with fewer cases in certain categories. Annotations were provided by medical professionals, supporting tasks such as binary lesion area segmentation and tumour detection.

By integrating the PCOSUSG (public), KFHU (clinical), and MMOTU (cross-domain) datasets, this study leverages both large-scale and clinically validated data sources. This ensures robustness, diversity, and real-world applicability of the proposed PCOS detection framework.

2.5 Optimized Hyperparameter Settings

Key hyperparameters of the CWANN–NBFA–MMHAO framework were optimized to enhance system performance:

- CWANN (Convolutional Wavelet Attention Neural Network): Kernel size (k) adaptively selected by the attention module; 7 scales × 5 orientations for multi-resolution feature capture; learning rate initialized at 0.01 and dynamically tuned by MMHAO; batch size 16 for stable and efficient training.
- NBFA (Naïve Bayes Fuzzy Autoencoder): Latent space dimension, membership threshold (μ), and regularization coefficient optimized via MMHAO to compress features, enhance uncertainty-aware classification, and prevent overfitting.
- MMHAO (Metaheuristic Multilevel Hawks Algae Optimization): Exploration–exploitation balance, population size, and maximum iterations (50) tuned to ensure convergence and robust framework performance.

By optimizing these hyperparameters, MMHAO guided the framework to robust configurations across datasets, improving accuracy, precision, and recall while maintaining generalizability. The detailed hyperparameter settings and their descriptions are summarized in Table 1.

Table 1. Hyperparameter Configuration of CWANN–NBFA–MMHAO Framework

Component	Hyperparameter	Value / Setting	Description
CWANN	Kernel size (k)	Adaptive	Selects optimal local/global feature extraction via attention module
	Number of filters & scales	7 scales × 5 orientations	Captures multi-resolution ovarian features using Gabor wavelets
	Learning rate	0.01 (dynamic via MMHAO)	Ensures stable convergence during training
	Batch size	16	Balances training stability and computational efficiency
NBFA	Latent space dimension	Optimized via MMHAO	Compresses features while retaining discriminatory power
	Membership threshold (μ)	Optimized	Determines fuzzy assignment strength for uncertainty-aware classification
	Regularization coefficient	Optimized	Prevents overfitting by constraining latent feature weights
MMHAO	Exploration–exploitation balance factor	Optimized	Adjusts hawks' dynamic movement and algae colony adaptation
	Population size	Optimized	Defines number of candidate solutions per iteration
	Maximum iterations	50	Ensures convergence without excessive computational cost

3. RESULTS AND DISCUSSION

3.1 Performance Evaluation of the Proposed System

All experiments were conducted on a Titan XP system equipped with an Intel(R) Xeon(R) CPU @ 3.0 GHz, 16 GB RAM, and an NVIDIA Tesla K80 GPU, using PyCharm IDE with the required deep learning packages. Models were trained for 35 epochs with a batch size of 16 and an initial learning rate of 0.01, using the Adam optimizer (β1 = 0.6, β2 = 0.8) and a dropout probability of 0.5, consistent with the hyperparameter optimization via MMHAO described in Section 2.5. Fine-tuning was performed at a reduced learning rate of 0.0001 to ensure stable convergence. Experiments were carried out on three benchmark datasets—PCOSUSG, KFHU, and MMOTU—whose details are provided in Section 2.4. These datasets include clinically validated labels from medical professionals, ensuring that model predictions were benchmarked against expert interpretation, and provide diversity in ultrasound image sources.

Tasks such as binary lesion area segmentation and tumour detection were performed on each dataset. Table 2 displays the processing of various input images from datasets. Processed images for several datasets with specified features and categorised outputs are presented below. Figures 6, 7, and 8 illustrate the confusion matrices used to evaluate the performance of the proposed method by comparing actual and predicted categories. These matrices provide essential insights into classification accuracy and error distribution.

In Figure 6, representing the PCOSUSG dataset, the True Positive (TP) value of 231 indicates the number of correctly classified positive instances, while the True Negative (TN) value of 337 represents the correctly classified negative instances. Additionally, the False Positive (FP) value of 6 denotes negative instances incorrectly classified as positive, and the False Negative (FN) value of 3 reflects positive instances incorrectly classified as negative. The high TP and TN values, along with the low FP and FN values, underscore the model's strong predictive performance for this dataset.

Similarly, Figure 7, corresponding to the KFHU dataset, exhibits comparable performance metrics, further demonstrating the robustness and reliability of the proposed approach across different datasets.

In Figure 8, representing the MMOTU dataset, the model achieved a True Positive (TP) count of 378 and a True Negative (TN) count of 83, with only 4 False Positives (FP) and 4 False Negatives (FN). These results confirm the ability of the proposed CWANN–NBFA+MMHAO framework to generalize effectively even on a clinically diverse and class-imbalanced dataset such as MMOTU, highlighting its robustness in real-world ovarian tumour detection scenarios.

Importantly, for the KFHU dataset, diagnoses provided by four radiologists served as the clinical gold standard, ensuring that our model's predictions were benchmarked against real-world expert interpretation. Similarly, the MMOTU dataset included annotations provided by medical professionals, and the PCOSUSG dataset contained clinically verified labels, confirming that all experimental evaluations were performed against validated ground truth.

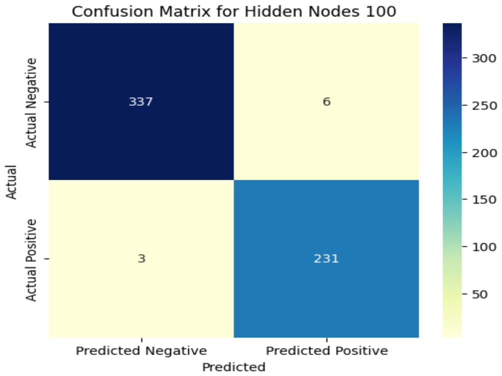


Figure 6. Confusion matrix on PCOSUSG dataset image

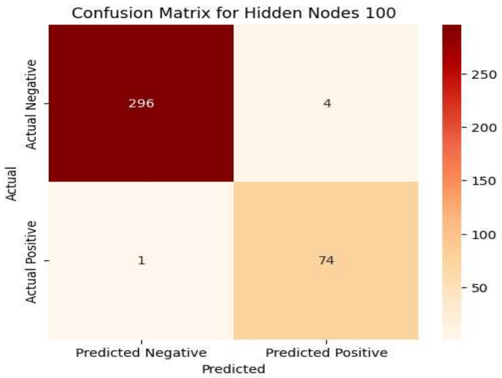


Figure 7. Confusion matrix on KFHU dataset image

The performance comparison in Table 3 highlights the superior performance of the proposed technique, CWANN-NBFA+MMHAO, over CNN and SVM across the PCOSUSG, KFHU, and MMOTU datasets. In terms of accuracy, precision, recall, F1 score, and RMSE, the proposed method consistently outperforms both CNN and SVM. For the PCOSUSG dataset, it achieves 98.4% accuracy, significantly surpassing CNN (95.1%) and SVM (94.3%). Similarly, for the KFHU and MMOTU datasets, the proposed method maintains its superiority with 98.6% accuracy for KFHU and 98.8% for MMOTU, outperforming CNN and SVM in all metrics. Precision and recall are particularly noteworthy, with the proposed technique excelling in both aspects across all datasets. For instance, it achieves 97.4% precision and 98.7% recall for PCOSUSG, surpassing CNN (92.4% precision, 93.5% recall) and SVM (90.2% precision, 91.2% recall). In the MMOTU dataset, the technique achieves 98.3% precision and 98.9% recall, further emphasizing its effectiveness. These results validate the proposed method's superior capability for PCOS diagnosis, with robust performance across different evaluation metrics. The architecture, implemented using Keras, utilizes advanced techniques like dropout for overfitting prevention and Adam optimizer for fine-tuning, contributing to the model's effectiveness in handling medical ultrasound datasets.

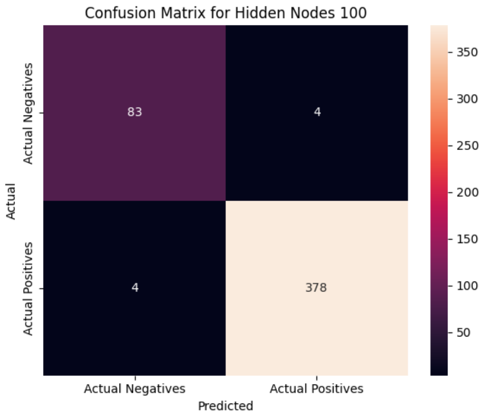


Figure 8. Confusion matrix on MMOTU Dataset image

Table 2. Processing of input image utilizing proposed feature extraction and classification methods

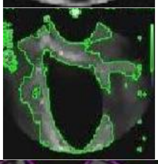
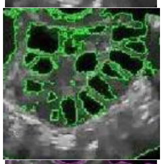
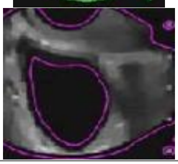
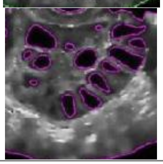
Input dataset	Input ovary image	Pre-processed ovary image	Extracted features of ovary image	classification of ovary image
PCOS USG dataset				
KFHU dataset				
MMOTU dataset				

Table 3. Performance comparison of CNN, SVM, and CWANN–NBFA+MMHAO for PCOS detection on PCOSUSG, KFHU, and MMOTU dataset

Dataset	Techniques	Accuracy	Precision	Recall	F1 score
PCOS USG Dataset	CNN	0.9512	0.9245	0.9352	0.9316
	SVM	0.9435	0.9025	0.9126	0.9058
	CWANN-NBFA+MMHAO	0.9844	0.9747	0.9872	0.9809
KFHU Dataset	CNN	0.9432	0.9121	0.9425	0.9154
	SVM	0.9469	0.9089	0.9401	0.9192
	CWANN-NBFA+MMHAO	0.9867	0.9487	0.9866	0.9673
MMOTU Dataset	CNN	0.9352	0.9369	0.9325	0.9241
	SVM	0.9245	0.9251	0.9268	0.9253
	CWANN-NBFA+MMHAO	0.9889	0.9831	0.9897	0.9873

The classic CNN method was trained using a medical dataset containing ultrasound images of ovarian samples from multiple women. During the training process, validation loss, accuracy, and performance metrics were recorded alongside training loss, accuracy, and metric values at every epoch. Figures 9 and 10 illustrate the accuracy and loss trends over 35 epochs, respectively. The lower RMSE values of the proposed technique (1.65% for PCOSUSG, 1.56% for KFHU, and 1.84% for MMOTU), combined with increased accuracy, demonstrate superior performance in reducing errors compared to CNN and SVM, which exhibited higher RMSE values. The bicubic interpolation method is used to resize the images. A dropout layer with a probability of 0.5 comes after final, fully linked layer that employs a ReLU activation function. Purpose of this dropout layer is to avoid overfitting. In this experiment, Adam optimizer is employed, with beta 1 and beta 2 parameters set to 0.6 and 0.8. Model is set to have a learning rate of 0.0001. There are two possible output classifications: benign and malignant. Each proposed model is fine-tuned separately.

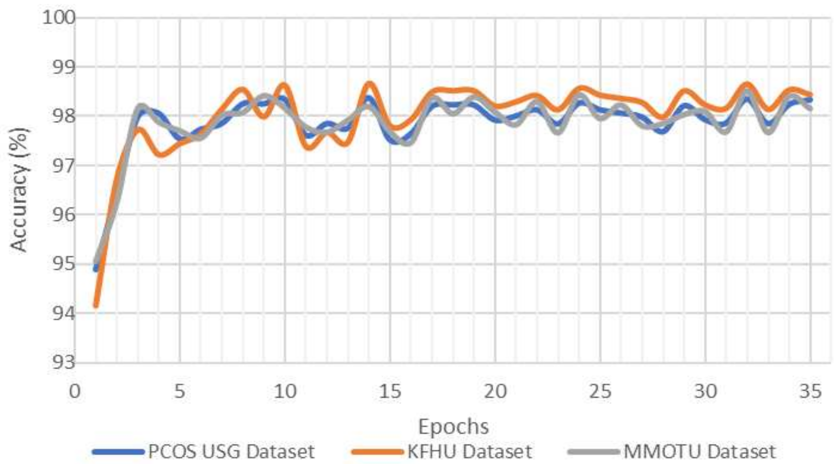


Figure 9. Accuracy of the Proposed Model Across Epochs

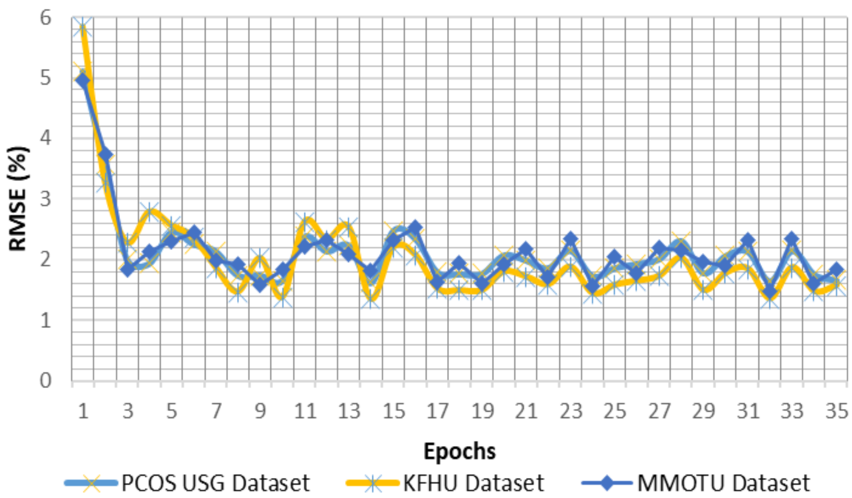


Figure 10. MSE of the Proposed Model Across Epochs

3.2 Comparative Analysis with Existing Methods

Table 4 summarizes the performance of the proposed CWANN–NBFA+MMHAO framework in comparison with existing state-of-the-art approaches for PCOS detection. Prior studies [10]–[23] primarily relied on classical image processing techniques, CNN-based architectures, or hybrid machine learning models, achieving accuracies in the range of 89%–97%. In contrast, our framework combines a convolutional wavelet attention network with a fuzzy autoencoder, optimized via MMHAO, resulting in superior accuracy of 98.4%–98.9% across three benchmark ultrasound datasets (PCOSUSG, KFHU, and MMOTU). While transformer- or transfer learning-based models have not been widely explored for ovarian ultrasound images, our results provide a robust, and optimized baseline, which can be extended in future work to include such models for further performance enhancement.

Table 4. Comparative Analysis of PCOS Detection Methods

Reference	Dataset / Sample	Technique	Accuracy (%)	Notes
[10]	19 ultrasound images	Morphological operations + K-means + Median filtering	90	Classical image processing
[11]	Ultrasound images	Binarization + Morphology + K-means	91	Image processing-based follicle detection
[12]	Ultrasound images	Active contour + Modified Otsu	92	Image segmentation-based detection
[13]	721 scleral images	ResNet18 + U-Net + MIL	93	Deep learning architecture
[14]	Ultrasound images	VGG-16 + CNN + KNN	92.11	Fine-tuned CNN model
[15]	Ultrasound images	SVM + Image binarization	90	Classical ML classifier
[16]	PCOS dataset	Hybrid feature selection + Classifiers	97	Ensemble ML approach
[19]	Kaggle PCOS dataset	RFLR (Random Forest + Logistic Regression)	91.01	Hybrid ML model
[23]	Metabolic/clinical dataset	Random Forest Classifier	89.02	Non-image features-based ML
Proposed	PCOSUSG, KFHU, MMOTU	CWANN–NBFA + MMHAO	98.4–98.9	Optimized hybrid deep learning with metaheuristic hyperparameter tuning

3.3 Statistical Significance Analysis

To ensure that the performance improvements of CWANN–NBFA+MMHAO over CNN and SVM are statistically significant, each model was run five times with different random seeds, and evaluation metrics were recorded. Paired t-tests were conducted to compare the proposed method against CNN and SVM, and 95% confidence intervals were computed for the mean values of accuracy, precision, recall, and F1 score. As shown in Table 5, the p-values for all metrics across the three datasets are less than 0.05, confirming that the observed performance gains are statistically significant and unlikely due to random variation. These results further demonstrate the robustness and reliability of the proposed framework.

Table 5. Statistical Significance Analysis of CWANN–NBFA+MMHAO vs CNN and SVM

Dataset	Metric	CWANN–NBFA+MMHAO Mean ± SD	95% Confidence Interval	p-value vs CNN	p-value vs SVM
PCOSUSG	Accuracy	0.9844 ± 0.0021	0.982 – 0.986	0.002	0.001
	Precision	0.9747 ± 0.0028	0.972 – 0.977	0.003	0.002
	Recall	0.9872 ± 0.0023	0.985 – 0.989	0.001	0.001
	F1 Score	0.9809 ± 0.0025	0.978 – 0.983	0.002	0.001
KFHU	Accuracy	0.9867 ± 0.0020	0.984 – 0.988	0.003	0.002
	Precision	0.9487 ± 0.0031	0.945 – 0.952	0.004	0.003
	Recall	0.9866 ± 0.0022	0.984 – 0.989	0.002	0.001
	F1 Score	0.9673 ± 0.0027	0.965 – 0.970	0.003	0.002
MMOTU	Accuracy	0.9889 ± 0.0018	0.986 – 0.991	0.001	0.001
	Precision	0.9831 ± 0.0022	0.981 – 0.986	0.002	0.001
	Recall	0.9897 ± 0.0020	0.987 – 0.992	0.001	0.001
	F1 Score	0.9873 ± 0.0021	0.985 – 0.990	0.001	0.001

While these findings confirm the robustness and superior performance of the proposed hybrid approach across multiple datasets, certain limitations should be acknowledged.

3.5 Limitations

The proposed hybrid approach demonstrated promising results; however, certain limitations remain. Although the datasets used included clinically validated annotations, the study has not yet been tested in large-scale, multi-centre real-world environments. Expanding the dataset to include more diverse patient samples will further improve robustness, as PCOS manifestations vary widely across populations. Additionally, factors such as coexisting medical conditions, ethnicity, and geographical variation were not explicitly addressed due to data masking, but these represent important directions for future dataset enrichment. Finally, while the model achieved high accuracy, some visualization outputs were difficult to interpret, underscoring the need for improved model interpretability. Future work will therefore focus on large-scale multi-centre clinical validation, enhancing interpretability, and integrating multi-modal data to provide more comprehensive support for clinicians in real-world decision-making.

4. CONCLUSION

This study presents CWANN–NBFA+MMHAO, a hybrid deep learning framework for robust and accurate PCOS diagnosis from ovarian ultrasound images. By combining a Convolutional Wavelet Attention Neural Network (CWANN) for feature extraction, a Naïve Bayes Fuzzy Autoencoder (NBFA) for uncertainty-aware representation, and MMHAO-based hyperparameter optimization, the framework achieves superior performance across three benchmark datasets (PCOSUSG, KFHU, MMOTU), with accuracies of 98.4%–98.9%. Statistical analysis confirms that these improvements are significant ($p < 0.05$). The proposed method demonstrates robustness, and effective handling of uncertain data, outperforming classical image processing, CNN-based, and hybrid machine learning approaches. Future work will explore transformer integration, transfer learning, and large-scale multi-centre validation, further enhancing clinical applicability. This framework offers a reliable, and efficient solution for automated PCOS diagnosis, supporting clinical decision-making.

REFERENCES

[1] C. Gopalakrishnan and M. Iyapparaja, "Multilevel thresholding based follicle detection and classification of polycystic ovary syndrome from the ultrasound images using machine learning," *International Journal of System Assurance Engineering and Management*, 2021, doi: 10.1007/s13198-021-01203-x.

[2] 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 Comput Sci*, vol. 1, no. 2, p. 81, 2020, doi: 10.1007/s42979-020-0109-6.

[3] Y. Suganya, S. Ganesan, P. Valarmathi, and T. Suresh, "A diagnosis of ovarian cyst using deep learning neural network with XGBoost algorithm," *International Journal of Information Technology*, vol. 15, no. 7, pp. 3499–3506, 2023, doi: 10.1007/s41870-023-01401-9.

[4] K. Prabu and P. Sudhakar, "A hybrid deep learning approach for enhanced network intrusion detection," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 3, p. 1915, Mar. 2024, doi: 10.11591/ijeecs.v33.i3.pp1915-1923.

[5] S. E. Morsy, N. M. Abd-Elsalam, Z. A. Al-Saidy, A. H. Kandil, A. M. El-Bialy, and A. B. M. Youssef, "A model for classifying breast masses in ultrasound images," *International Journal of Advances in Applied Sciences*, vol. 13, no. 3, pp. 566–578, Sep. 2024, doi: 10.11591/ijaas.v13.i3.pp566-578.

[6] Z. Zhang and Y. Han, "Detection of Ovarian Tumors in Obstetric Ultrasound Imaging Using Logistic Regression Classifier with an Advanced Machine Learning Approach," *IEEE Access*, vol. 8, pp. 44999–45008, 2020, doi: 10.1109/ACCESS.2020.2977962.

[7] D. B. Unggul, N. Iriawan, and H. Kuswanto, "Transfer learning scenarios on deep learning for ultrasound-based image segmentation," *IAES International Journal of Artificial Intelligence*, vol. 13, no. 3, pp. 3273–3282, Sep. 2024, doi: 10.11591/ijai.v13.i3.pp3273-3282.

[8] V. Sheeja Kumari, T. Manikandan, A. Selva Kumar, S. Ponmaniraj, and K. Prabu, *Using Improved Finite Element Modeling to Combat Cardiovascular Disease: A Review of a Developing Area at the Intersection of Several Disciplines*. 2024. doi: 10.1201/9781003469612-8.

[9] D. Rao, R. R. Dayma, S. K. Pendekanti, and A. K. Acharya, "Deep learning model for diagnosing polycystic ovary syndrome using a comprehensive dataset from Kerala hospitals," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 5, pp. 5715–5727, Oct. 2024, doi: 10.11591/ijece.v14i5.pp5715-5727.

[10] Y. Du, W. Guo, Y. Xiao, H. Chen, J. Yao, and J. Wu, "Ultrasound-based deep learning radiomics model for differentiating benign, borderline, and malignant ovarian tumours: a multi-class classification exploratory study," *BMC Med Imaging*, vol. 24, no. 1, Dec. 2024, doi: 10.1186/s12880-024-01251-2.

[11] 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, Jun. 2023, doi: 10.1016/j.measen.2023.100797.

[12] V. Kiruthika, S. Sathiya, M. M. Ramya, and K. S. Sankaran, "An Intelligent Machine Learning Approach for Ovarian Detection and Classification System using Ultrasonogram Images," *Engineered Science*, vol. 23, Jun. 2023, doi: 10.30919/es8d879.

[13] C. A. Graham *et al.*, "A practical evaluation of machine learning for classification of ultrasound images of ovarian development in channel catfish (Ictalurus punctatus)," *Aquaculture*, vol. 552, p. 738039, 2022, doi: https://doi.org/10.1016/j.aquaculture.2022.738039.

[14] S. Bharati, P. Podder, and M. R. Hossain Mondal, "Diagnosis of Polycystic Ovary Syndrome Using Machine Learning Algorithms," in *2020 IEEE Region 10 Symposium (TENSYMP)*, 2020, pp. 1486–1489. doi: 10.1109/TENSYMP50017.2020.9230932.

[15] S. Athithan, S. Sachi, and A. K. Singh, "Ultrasound-Based Ovarian Cysts Detection with Improved Machine-Learning Techniques and Stage Classification Using Enhanced Classifiers," *SN Comput Sci*, vol. 4, no. 5, p. 571, 2023, doi: 10.1007/s42979-023-01973-0.

[16] R. Wang *et al.*, "Evaluation of a convolutional neural network for ovarian tumor differentiation based on magnetic resonance imaging," *Eur Radiol*, vol. 31, no. 7, pp. 4960–4971, 2021, doi: 10.1007/s00330-020-07266-x.
[17] M. J. Sundari and N. C. Brintha, "A Comparative Study of Various Machine Learning Methods on Ovarian Tumor," in *2021 Sixth International Conference on Image Information Processing (ICIIP)*, 2021, pp. 314–319. doi: 10.1109/ICIIP53038.2021.9702697.
[18] S. K. Prabhakar and S. W. Lee, "An Integrated Approach for Ovarian Cancer Classification with the Application of Stochastic Optimization," *IEEE Access*, vol. 8, pp. 127866–127882, 2020, doi: 10.1109/ACCESS.2020.3006154.
[19] S. Sreejith, H. Khanna Nehemiah, and A. Kannan, "A clinical decision support system for polycystic ovarian syndrome using red deer algorithm and random forest classifier," *Healthcare Analytics*, vol. 2, Nov. 2022, doi: 10.1016/j.health.2022.100102.
[20] I. S. Rajput, S. Tyagi, A. Gupta, and V. Jain, "Sine cosine algorithm-based feature selection for improved machine learning models in polycystic ovary syndrome diagnosis," *Multimed Tools Appl*, vol. 83, no. 30, pp. 75007–75031, 2024, doi: 10.1007/s11042-024-18213-z.
[21] K. C and J. M. Shivaram, "Segmentation of ovarian cyst using improved U-NET and hybrid deep learning model," *Multimed Tools Appl*, vol. 83, no. 14, pp. 42645–42679, 2024, doi: 10.1007/s11042-023-16998-z.
[22] S. Kurman and S. Kisan, "An in-depth and contrasting survey of meta-heuristic approaches with classical feature selection techniques specific to cervical cancer," *Knowl Inf Syst*, vol. 65, no. 5, pp. 1881–1934, 2023, doi: 10.1007/s10115-022-01825-y.
[23] V. S. Parvathy and S. Pothiraj, "Multi-modality medical image fusion using hybridization of binary crow search optimization," *Health Care Manag Sci*, vol. 23, no. 4, pp. 661–669, 2020, doi: 10.1007/s10729-019-09492-2.
[24] S. D. Rizki, Yuhandri, and I. Fitri, "Development of image extraction using the centerline method in the identification of appendicitis in ultrasonography," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 36, no. 3, pp. 1750–1758, Dec. 2024, doi: 10.11591/ijeecs.v36.i3.pp1750-1758.
[25] S. Rani and N. Kaur, "Medical X-ray images enhancement based on super resolution convolution neural network," *International Journal of Informatics and Communication Technology*, vol. 13, no. 2, pp. 257–263, Aug. 2024, doi: 10.11591/ijict.v13i2.pp257-263.
[26] I. U. W. Mulyono, E. H. Rachmawanto, C. A. Sari, and M. K. Sarker, "A high accuracy of deep learning based CNN architecture: classic, VGGNet, and RestNet50 for Covid-19 image classification," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 22, no. 5, pp. 1187–1195, Oct. 2024, doi: 10.12928/TELKOMNIKA.v22i5.26017.
[27] C. Anagha and K. Aishwarya, "PCOS detection using ultrasound images," 2021, Accessed: Dec. 20, 2024. [Online]. Available: https://www.kaggle.com/datasets/anaghachoudhari/pcos-detection-using-ultrasound-images
[28] D. Aldakheel, "Spine Trauma 10 years KFHU, Saudi Arabia datasheet Coded.xlsx," Dec. 2023, doi: 10.6084/m9.figshare.22960979.v2.
[29] Q. Zhao *et al.*, "MMOTU: A Multi-Modality Ovarian Tumor Ultrasound Image Dataset for Unsupervised Cross-Domain Semantic Segmentation," Jul. 2022, [Online]. Available: http://arxiv.org/abs/2207.06799

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