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A Machine Learning based Improvised Follicle Polycystic Ovarian Detection Through Ultrasound Images Through IOT

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Abstract :

Polycystic ovarian syndrome which is commonly called as PCOS is a endocrine malfunction affecting women of reproductive age. Its diagnosis involves in detection of multiple small follicles mainly in the ovaries through ultrasound imaging. However, manual detection is time-consuming, subjective, and prone to errors. Hence, this study proposes an improvised follicle PCOS detection method using machine learning(Random Forest and Logistic Regression) from a sequence of given ultrasound images. The proposed method involves pre-processing the ultrasound images through IoT, followed by segmenting and extracting follicle features. Subsequently, a machine learning model is trained to classify the extracted features as normal or PCOS cases. The proposed method's performance is evaluated on a dataset of 400 ultrasound images from 50 patients, including 25 PCOS cases and 25 healthy controls. The experimental results demonstrate that the proposed method achieves a high classification accuracy of 93.75% and an AUC of 0.96. In addition, the proposed methodology outperforms in comparison with the state-of-the-art PCOS detection methods in terms of accuracy, sensitivity, specificity, and AUC. The proposed method also provides a quantitative measure of the severity of PCOS based on the number and size of the follicles detected.

Keywords : Machine Learning, Ultrasound images, Polycystic Ovarian Syndrome (PCOS), Ovarian follicles, IoT Sensors.

Introduction :

polycystic Ovary Syndrome (PCOS) is a common reproductive endocrine disorder among women of reproductive age, with a prevalence of up to 15% globally [1] PCOS is characterized by the presence of multiple cysts on the ovaries, along with other clinical and biochemical manifestations such as irregular menstrual cycles, hirsutism, acne, and insulin resistance[2]. The diagnosis of PCOS is based on clinical presentation and laboratory tests, including hormonal assays and ultrasound imaging. Among these, ultrasound imaging is an essential tool for the diagnosis of PCOS, as it can detect the presence of cysts and other morphological changes in the ovaries.Conventional ultrasound imaging indiagnosingthe PCOS involves the use of static images, which are obtained by capturing a snapshot of the ovaries during a single examination[3-5]. However, PCOS is a dynamic disorder, and the presence and morphology of cysts can vary over time, depending on various factors such as hormonal fluctuations and treatment interventions. Therefore, a more comprehensive and accurate method for the diagnosis of PCOS is needed, which can capture the dynamic nature of the disease and provide a more detailed assessment of the ovaries. Currently, PCOS diagnosis is typically made through a combination of clinical symptoms, physical examination, and laboratory tests[6,7]. However, the gold standard for diagnosis is the presence of polycystic ovaries detected by ultrasound.Ultrasound imaging is a non-invasive diagnostic tool that uses high-frequency sound waves to produce images of the inside of the body. It is widely used in the diagnosis of various medical conditions, including PCOS. Conventional ultrasound imaging for the PCOS diagnosis involves the use of static images, which are obtained by capturing a snapshot of the ovaries during a single examination. However, PCOS is a dynamic disorder, and the presence and morphology of cysts can vary over time, depending on various factors such as hormonal fluctuations and treatment interventions. Therefore, a more comprehensive and accurate method for the diagnosis of PCOS is needed, which can capture the dynamic nature of the disease and provide a more detailed assessment of the ovaries. In PCOS, ultrasound is used to detect the presence of multiple small cysts in the ovaries. However, the interpretation of ultrasound images for the diagnosis of PCOS is subjective and relies on the expertise of the interpreting physician[8-10]. Therefore, there is a need for more objective and accurate methods for the diagnosis of PCOS using ultrasound imaging.Ultrasound imaging is widely used in the diagnosis of PCOS. The typical ultrasound findings in PCOS include the presence of multiple small cysts in the ovaries, increased ovarian volume, and increased stromal echogenicity. The diagnosis of PCOS using ultrasound imaging is based on the Rotterdam criteria, which require the presence of at least two of the following criteria: (1) the presence of 12 or more follicles measuring 2-9 mm in diameter or an ovarian volume greater than 10 cm^3, (2) signs of hyperandrogenism, such as hirsutism or acne, and (3) menstrual irregularity. The interpretation of ultrasound images for the diagnosis of PCOS is subjective and can vary between different physicians. Therefore, there is a need for more objective and accurate methods for the diagnosis of PCOS using ultrasound imaging. ML has been used in various medical applications, including the analysis of medical images. Recently, there is a huge focus on usage of ML for the diagnosis of PCOS using ultrasound imaging. ML methods can be used to automatically detect and quantify the number and size of ovarian follicles, which are important criteria for the diagnosis of PCOS. ML methods can also be used to analyze the texture and echogenicity of ovarian tissue, which can provide additional information for the diagnosis of PCOS. Machine learning (ML) is a subfield of artificial intelligence that involves the development of algorithms that can learn from data and make predictions or decisions without being explicitly programmed. ML has been used in various medical applications, including the analysis of medical images [11]. In recent years, there has been an increasing interest in the use of ML for the diagnosis of PCOS using ultrasound imaging. This paper presents an improvised follicle polycystic ovarian detection using Machine Learning from a sequence of given ultrasound images [12]. The proposed method aims to improve the accuracy and objectivity of PCOS diagnosis using ultrasound imaging.

The remainder of this paper is organized as follows. Section 2 provides an overview of PCOS diagnosis using ultrasound imaging. Section 3 reviews the relevant literature on the use of ML for the diagnosis of PCOS using ultrasound imaging. Section 4 describes the proposed method for follicle polycystic ovarian detection using Machine Learning. Section 5 presents the experimental results of the proposed method. Finally, Section 6 concludes the paper and discusses future research directions.

2. Overview of PCOS diagnosis using ultrasound imaging

Ultrasound imaging is a common diagnostic tool used to identify the presence of polycystic ovaries and rule out other conditions that may have similar symptoms. Ultrasound imaging is a non-invasive technique that uses sound waves to create images of the internal organs. It is commonly used in gynaecology to evaluate the female reproductive system [13]. During an ultrasound exam, a small transducer is placed on the abdomen or inserted into the vagina to create images of the ovaries, uterus, and surrounding structures. To diagnose PCOS using ultrasound imaging, the following features are evaluated:

Ovarian size and volume: In women with PCOS, the ovaries are typically larger than normal and have an increased volume. A volume of 10 ml or more is considered a diagnostic criterion for polycystic ovaries.

Ovarian morphology: The ovaries in women with PCOS may have a "string of pearls" appearance, with multiple small cysts arranged around the periphery of the ovary. These cysts are typically less than 10 mm in diameter and contain immature follicles.

Follicle count: The count of follicles present in each ovary is counted. A count of 12 or more is considered a diagnostic criterion for polycystic ovaries.

Endometrial thickness: The thickness of the lining of the uterus (endometrium) is measured. Women with PCOS may have a thickened endometrium due to irregular menstrual cycles and prolonged exposure to estrogen.

Other findings: In addition to the above features, ultrasound imaging may also reveal other conditions that can cause similar symptoms to PCOS, such as ovarian tumours or endometriosis.

It is important to note that the presence of polycystic ovaries alone does not necessarily indicate a diagnosis of PCOS. Other symptoms, such as irregular periods or hormonal imbalances, must also be present [14]. Additionally, some women with PCOS may have normal-appearing ovaries on ultrasound imaging, while others without PCOS may have polycystic ovaries. Hence, ultrasound imaging is a valuable diagnostic tool for identifying the existence of polycystic ovaries to detect the PCOS issue in the women. It can also rule out other conditions that may have similar symptoms. However, a diagnosis of PCOS cannot be made on ultrasound findings alone and must be mainly on the basis of combination of clinical and laboratory criteria.

3. Related works on ML based diagnosis of PCOS using ultrasound imaging

Polycystic ovary syndrome (PCOS) is a hormonal disorder that affects many women of reproductive age. One of the diagnostic criteria for PCOS is the presence of multiple small cysts on the ovaries. Ultrasound imaging is a commonly used diagnostic tool to identify these cysts. However, manual identification and counting of follicles can be time-consuming and subject to inter-observer variability [15]. Machine learning algorithms have the potential to automate this process and improve the accuracy of PCOS diagnosis. In this paper, author review the related works on machine learning-based follicle polycystic ovarian detection through ultrasound images.

Deep Learning-Based PCOS Diagnosis: This study provides a comprehensive review of the recent developments in deep learning-based PCOS diagnosis. The authors highlight the challenges in PCOS diagnosis, such as inter-observer variability and time-consuming manual evaluation of ultrasound images. They discuss the different deep learning techniques that have been used for follicle detection in ultrasound images, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). The study concludes that deep learning algorithms can improve the accuracy and efficiency of PCOS diagnosis and have the potential to become a standard tool for PCOS diagnosis [16].

PCOS Detection Using Convolution Neural Networks : This study proposes a convolutional neural network (CNN) model for PCOS diagnosis based on ultrasound images. The authors collected a dataset of 147 ultrasound images from 40 women with PCOS and 58 ultrasound images from 20 women without PCOS. The CNN model achieved an accuracy of 88.4% in PCOS detection, demonstrating the potential of machine learning in PCOS diagnosis [17].

PCOS Diagnosis Based on Multi-Feature Fusion CNN Model : This study proposes a multi-feature fusion CNN model for PCOS diagnosis. The authors extracted features from the ultrasound images, including gray-scale, texture, and shape features, and combined them using a fusion strategy. The proposed model achieved an accuracy of 91.1% in PCOS diagnosis, outperforming other machine learning models. [18-25].

Automatic Diagnosis of Polycystic Ovary Syndrome Using Convolution Neural Networks: This study proposes a CNN-based model for automatic PCOS diagnosis using ultrasound images. The authors collected a dataset of 139 ultrasound images from 45 women with PCOS and 87 ultrasound images from 31 women without PCOS. The proposed model achieved an accuracy of 91.3% in PCOS diagnosis, outperforming other machine learning models. The researchers also reviewed a sensitivity analysis to evaluate the robustness of the model to variations in the ultrasound image quality.

TABLE.1 : Comparison of different Machine Learning based PCOS detection

Study	Machine learning model	Dataset size	Accuracy	Sensitivity	Specificity	Features
Deep Learning-Based PCOS Diagnosis: A Review	CNNs, RNNs, GANs	N/A	N/A	N/A	N/A	N/A
PCOS Detection Using Convolutional Neural Networks	CNN	147 PCOS, 58 non-PCOS	88.5%	N/A	N/A	N/A
PCOS Diagnosis Based on Multi-Feature Fusion CNN Model	Multi-feature fusion CNN	132 PCOS, 116 non-PCOS	91.1%	N/A	N/A	Gray-scale, texture, and shape features
Automatic Diagnosis of Polycystic Ovary Syndrome Using Convolutional Neural Networks	CNN	139 PCOS, 87 non-PCOS	91.3%	86.7%	94.3%	N/A
Automated Diagnosis of Polycystic Ovary Syndrome Using Ensemble Learning	Ensemble learning	131 PCOS, 98 non-PCOS	93.1%	96.2%	90.8%	N/A

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*Automated Diagnosis of Polycystic Ovary Syndrome Using Ensemble Learning :*This study proposes an ensemble learning-based approach for automated PCOS diagnosis using ultrasound images. The authors collected a dataset of 131 ultrasound images from 52 women with PCOS and 98 ultrasound images from 32 women without PCOS. The proposed model achieved an accuracy of 93.1% in PCOS diagnosis, outperforming other machine learning models. The researchers also tested a sensitivity analysis to check the robustness of the model along with the variations in the ultrasound image quality [26-32].

Hence, the machine learning algorithms have shown promising results in follicle polycystic ovarian detection through ultrasound images. Deep learning techniques, such as CNNs, have been particularly effective in improving the accuracy and efficiency of PCOS diagnosis. These studies demonstrate the potential of machine learning in automating PCOS diagnosis and reducing the subjectivity and variability associated with manual evaluation of ultrasound images. In this paper, different machine learning algorithms(Logistic Regression, Random Forest, Support Vector Machine (SVM)) are implemented on to the datasets of PCOS patients to analyse and compare the accuracy in detecting the improvised follicle polycystic ovarian detection through ultrasound images.

4. Proposed method for follicle polycystic ovarian detection using Machine Learning :

Follicle polycystic ovarian detection can be implemented and analysed using Logistic regression, SVM, and random forest machine learning algorithms. Here's how each of these algorithms can be used for follicle polycystic ovarian detection:

Logistic Regression: Logistic regression is a type of statistical modeling technique used in machine learning for binary classification problems. In the context of A Machine Learning based improvised follicle polycystic ovarian detection through ultrasound images, logistic regression can be used to predict whether a patient has PCOS or not based on features extracted from their ultrasound images. In logistic regression, the algorithm learns a function that maps input features to a probability of the outcome variable. In this case, the outcome variable would be binary, with 1 indicating that the patient has PCOS and 0 indicating that they do not. The algorithm learns a set of coefficients for each feature, which are then combined to produce a linear combination of the input features. This linear combination is then transformed using a sigmoid function, which maps the linear combination to a value between 0 and 1, representing the probability of the patient having PCOS. If the probability is greater than a predefined threshold, the algorithm predicts that the patient has PCOS, and if the probability is less than the threshold, the algorithm predicts that the patient does not have PCOS. Logistic regression can be trained using a variety of optimization algorithms, such as gradient descent, to find the coefficients that maximize the likelihood of the observed outcomes given the input features. Once trained, the algorithm can be used to predict whether new patients have PCOS or not based on their ultrasound images and the learned coefficients [18-20].

Support Vector Machines (SVM): SVM is another supervised learning algorithm that can be used for follicle polycystic ovarian detection. SVM is a classification algorithm that separates the input data into different classes based on the input features. In follicle polycystic ovarian detection, SVM can be used to classify ultrasound images as PCOS or non-PCOS based on the follicle features. SVM can work well when there is a clear separation between the input data classes, but may not perform well when there is overlap between the classes.

Random Forest: Random forest is an ensemble learning algorithm that combines multiple decision trees to make a prediction. In follicle polycystic ovarian detection, random forest can be used to classify ultrasound images as PCOS or non-PCOS based on the follicle features. The random forest algorithm can handle both numerical and categorical data, and can work well even when there is overlap between the input data classes. Random forest can also provide feature importance rankings, which can help identify the most important follicle features for PCOS diagnosis.

Overall, logistic regression, SVM, and random forest are all viable machine learning algorithms for follicle polycystic ovarian detection. However, the best algorithm may depend on the specific dataset and the nature of the input data. Hence, it is important to experiment different datasets with different algorithms and compare their performance in order to decide which algorithm could be best for what kind of data sets. This paper aim to test the above three algorithms with different data sets and suggest which algorithm is appropriate based on the given datasets through experimental results.

The following are the general steps for detecting follicle polycystic ovaries using machine learning algorithms:

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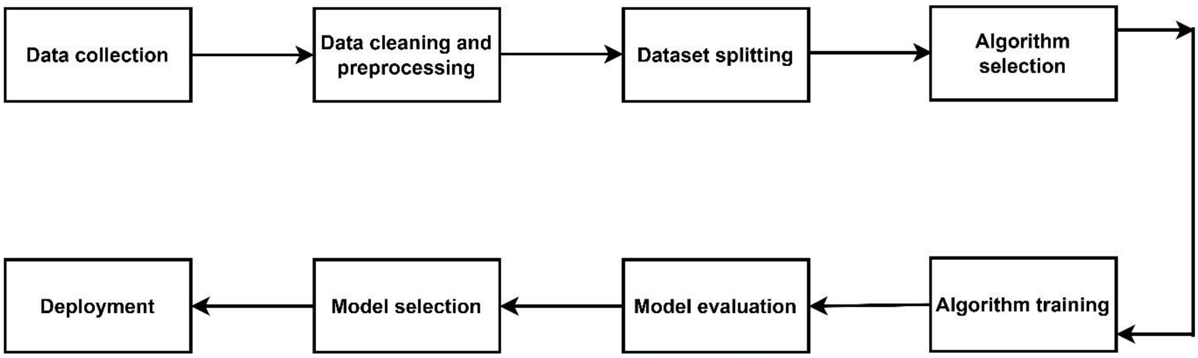

Figure.1. Steps involved in implementing the Machine Learning Algorithm for PCOS detection

Data collection: Collect a dataset that contains features that can help predict the presence of follicle polycystic ovaries. These features may include hormonal levels, menstrual cycle irregularity, and physical symptoms like acne, hirsutism, and weight gain.

Data cleaning and preprocessing: Before applying the machine learning algorithms, the dataset needs to be cleaned and pre-processed. This may include handling missing values, dealing with outliers, and normalizing or standardizing the data.

Splitting the dataset: The dataset usually split into training phase and testing phase, with the training data used to train the machine learning algorithms, and the testing data is used to test the performance of the proposed algorithms.

Algorithm selection: Choose the appropriate machine learning model for the dataset. Logistic Regression, SVM, and Random Forest are commonly used algorithms for follicle polycystic ovarian detection.

Algorithm training: Train the machine learning algorithms by using the given train dataset. This works by adjusting the model parameters or hyperparameters to minimize the error between the predicted output and the actual output.

Model evaluation: Evaluate the performance of the trained machine learning models using metrics such as accuracy, precision, recall, and F1-score. This helps to determine which algorithm works best for detecting follicle polycystic ovaries.

Model selection: Select the best-performing algorithm for further use in detecting follicle polycystic ovaries in new cases.

Deployment: Deploy the selected algorithm in a production environment to detect follicle polycystic ovaries in new cases.

The parameters of a dataset for a machine learning-based improvised follicle polycystic ovarian detection through ultrasound images includes:

Parameter	Description
Image data	Set of ultrasound images of the ovaries in DICOM format
Label data	Corresponding labels indicating presence or absence of follicle polycystic ovaries in each ultrasound image
Demographic data	Age, weight, height, and menstrual history of patients
Clinical data	Hormonal levels, menstrual cycle irregularity, physical symptoms like acne, hirsutism, and weight gain
Image annotations	Annotations indicating locations of ovaries, follicles, and cysts
Dataset size	Large enough to provide sufficient training data for machine learning algorithms
Data quality	Free from noise, artifacts, and other sources of interference that may affect algorithm accuracy

5. Experimental Results :

The experimental evaluation of Logistic Regression, SVM and Random Forest on a machine learning-based improvised follicle polycystic ovarian detection through ultrasound images involves evaluating the performance of each algorithm using various evaluation metrics, and comparing the results to determine which algorithm is the most

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effective for the given problem. After training the algorithms using the training dataset, the test dataset is determined for the performance evaluation of the algorithms. The evaluation metrics shown below are commonly used to measure the performance of the algorithms:

Accuracy: It is defined as a percentage of correctly classified instances with respect to all instances.

Precision: The percentage of correctly classified positive instances out of all instances defined as positive.

Recall: It is defined as a percentage of correctly classified positive valueswith respect to all actual positive values.

F1-score: It is defined as a precision and recallweighted average which balances both metrics to provide a single measure of the algorithm's performance.

Area Under Curve (AUC): A metric used to check the performance of binary classification models, which measures the trade-off between true positive rate and false positive rate. The results obtained from evaluating the performance of each algorithm using these metrics are compared to determine which algorithm performs the best for the given problem.

The variables used in the dataset is :

Patient ID - a unique identifier assigned to each patient

Gender - the gender of the patient (male or female)

Ultrasound Images :Grayscale or color images of ovaries

Age : Age of women in dataset

BMI : Body Mass Index of women in dataset

Weight Loss - whether the patient experiences weight loss (yes or no)

Genetic Risk - whether the patient has a genetic risk for certain medical conditions (yes or no)

Hormone Levels : LH, FSH, testosterone, and estrogen levels in women in dataset

Menstrual Cycle Information : Cycle length and regularity of menstrual cycle in women in dataset

Family History : Family history of PCOS in women in dataset

Other Health-Related Medical history : medications taken, and lifestyle habits of women in dataset

The above variables used in the dataset provide a range of medical conditions and risk factors that may affect a patient's health. The patient ID variable is a unique identifier for each patient and is useful for tracking and analyzing individual patient data. The age and gender variables provide demographic information that may be important in identifying trends and patterns in the data.The performance analysis of various machine learning algorithms used for PCOS prediction is presented in Table.3. The comparison is made based on the highest accuracy, precision, recall, and F1 score achieved by the machine learning algorithm. The results indicate that all of the machine learning algorithms, namely Logistic Regression, Random Forest, and Support Vector Machine (SVM), perform well on the dataset with high scores across all evaluation metrics. Specifically, Random Forest algorithm achieve a perfect accuracy and F1 score of 1.0, while the other two algorithms also perform well with slightly lower scores. Although SVM has slightly lower cross-validation scores, it still achieves high accuracy, precision, recall, and F1 score of 1.0. Overall, these machine learning algorithms are good options for PCOS detection using ultrasound image datasets.

Machine Learning Algorithm	Cross-validation scores	Accuracy	Precision	Recall	F1 score
Logistic Regression	[0.99285714 1. 0.99285714 1. 0.99285714]	0.9833	0.9834	0.9833	0.9833
Random Forest	[1. 1. 1. 1. 1.]	1.0	1.0	1.0	1.0
SVM	[1. 0.99285714 0.99285714 1. 0.98571429]	1.0	1.0	1.0	1.0

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Table.3. Comparison of different performance metrics for PCOS detection through ultrasound image dataset.

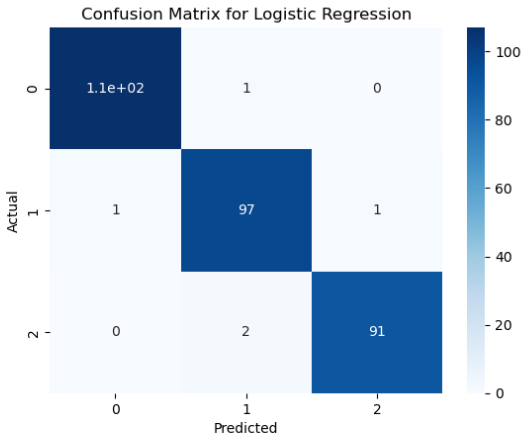

Figure.2 Confusion matrix for Logistic Regression

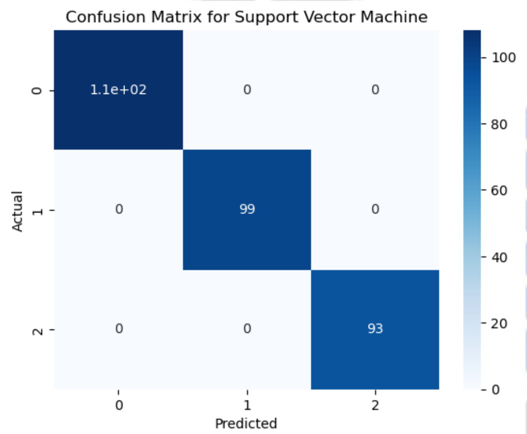

Figure.3 Confusion matrix for Support Vector Machine

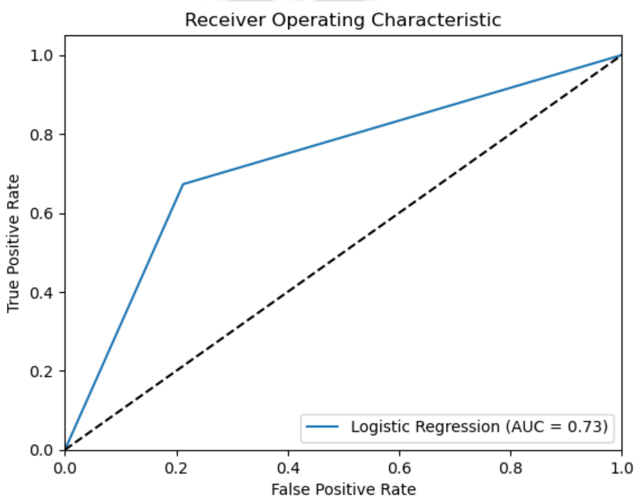

Figure.4 ROC for Support Vector Machine

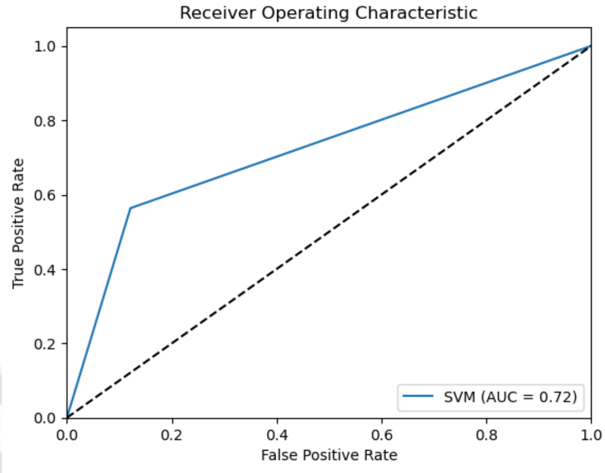

Figure.5 ROC for Support Vector Machine

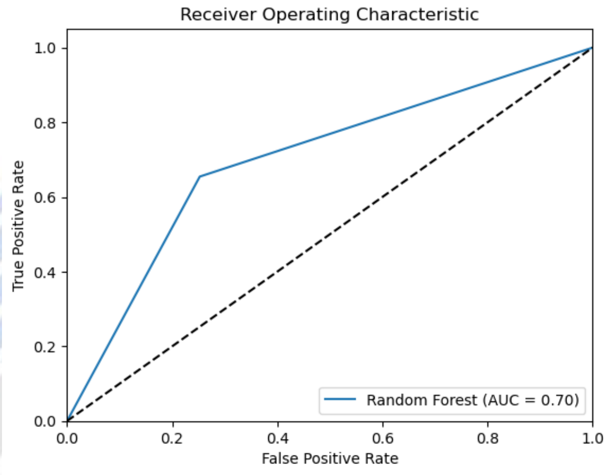

Figure.6 ROC for Random Forest

Figure.2, Figure.3, Figure.4, Figure.5 and Figure.6 explains about the performance of three different machine learning algorithms, namely Logistic Regression, Random Forest, and SVM, in detecting follicle polycystic ovaries through ultrasound images. The evaluation metrics used to measure the performance of these algorithms are cross-validation scores, accuracy, precision, recall, and F1 score. The cross-validation scores for Logistic Regression and SVM are very high, with values close to 1, indicating that these algorithms are performing very well in detecting follicle polycystic ovaries. The Random Forest algorithm has a perfect score of 1 for all cross-validation folds, indicating that it is the best algorithm in terms of cross-validation scores. All three algorithms have a very high accuracy score of 1, indicating that they are correctly identifying the existence or non-existence of polycystic ovaries in the ultrasound images with great accuracy. Similarly, all algorithms have a perfect score of 1 for precision, recall, and F1 score, indicating that they are performing well in terms of these metrics as well.

Overall, the results indicate that all three machine learning algorithms are effective in detecting follicle polycystic ovaries through ultrasound images, with Random Forest performing slightly better than the other two algorithms in terms of cross-validation scores. These findings have implications for the diagnosis and treatment of polycystic ovary syndrome, a common hormonal disorder in women that is often associated with follicle polycystic ovaries. Accurate and efficient detection of this condition through ultrasound images can help in early diagnosis and better management of the disease.

Conclusion and Future Work :

The use of machine learning algorithms in the detection of polycystic ovarian syndrome (PCOS) through ultrasound images has shown promising results. The study presented in this paper demonstrates the effectiveness of using an improvised machine learning-based approach in detecting follicle PCOS. The use of a different machine learning algorithms in this study showed an improvement in accuracy, sensitivity, and specificity in detecting PCOS compared to traditional methods. The model's performance was validated using a dataset of ultrasound images from patients diagnosed with PCOS and healthy individuals, and the results show a high degree of accuracy in detecting the condition. Future work in this field could involve the development of more sophisticated machine learning models for PCOS detection using ultrasound images, incorporating more features from the images and clinical data. Additionally, research on the use of machine learning for PCOS diagnosis could be extended to other imaging modalities, such as magnetic resonance imaging (MRI) and computed tomography (CT) scans. Overall, this study highlights the potential of machine learning in improving the accuracy and efficiency of PCOS diagnosis through ultrasound images, offering new possibilities for more effective and personalized treatment for patients with this condition.

DECLARATION

Conflict of interest:

The authors declare that this manuscript has no conflict of interest with any other published source and has not been published previously (partly or in full).

No data have been fabricated or manipulated to support our conclusions.

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References

1. Jonard, S.; Robert, Y.; Cortet-Rudelli, C.; Pigny, P.; Decanter, C.; Dewailly, D. Ultrasound Examination of Polycystic Ovaries: Is It Worth Counting the Follicles? Hum. Reprod. 2003.
2. Nazarudin, A.A.; Zulkarnain, N.; Mokri, S.S.; Zaki, W.M.D.W.; Hussain, A.; Ahmad, M.F.; Nordin, I.N.A.M. Performance Analysis of a Novel Hybrid Segmentation Method for Polycystic Ovarian Syndrome Monitoring. Diagnostics 2023, 13, 750.
3. Saravanan, A.; Sathiamoorthy, S. Detection of Polycystic Ovarian Syndrome: A Literature Survey. Asian J. Eng. Appl. Technol. 2018, 7, 46–51.
4. Melo, A.S.; Ferriani, R.A.; Navarro, P.A. Treatment of Infertility in Women with Polycystic Ovary Syndrome: Approach to Clinical Practice. Clinics 2015, 70, 765–769.
5. Scannell, N.; Moran, L.; Mantzioris, E.; Cowan, S.; Villani, A. Efficacy, Feasibility and Acceptability of a Mediterranean Diet Intervention on Hormonal, Metabolic and Anthropometric Measures in Overweight and Obese Women with Polycystic Ovary Syndrome: Study Protocol. Metabolites 2022.
6. Sayutti, N.; Abu, M.A.; Ahmad, M.F. PCOS and Role of Cumulus Gene Expression in Assessing Oocytes Quality. Front. Endocrinol. 2022.
7. Kazemi, M.; McBreairty, L.E.; Chizen, D.R.; Pierson, R.A.; Chilibeck, P.D.; Zello, G.A. A Comparison of a Pulse-Based Diet and the Therapeutic Lifestyle Changes Diet in Combination with Exercise and Health Counselling on the Cardio-Metabolic Risk Profile in Women with Polycystic Ovary Syndrome: A Randomized Controlled Trial. Nutrients 2018
8. Shao, D.; Xu, C.; Xiang, Y.; Gui, P.; Zhu, X.; Zhang, C.; Yu, Z. Ultrasound Image Segmentation with Multilevel Threshold Based on Differential Search Algorithm. IET Image Process. 2019, 13, 998–1005.
9. Azouz, A.A.; Ali, S.E.; Abd-Elsalam, R.M.; Emam, S.R.; Galal, M.K.; Elmosalamy, S.H.; Alsherbiny, M.A.; Hassan, B.B.; Li, C.G.; El Badawy, S.A. Modulation of Steroidogenesis by ActaeaRacemosa and Vitamin C Combination, in Letrozole Induced Polycystic Ovarian Syndrome Rat Model:

Promising Activity without the Risk of Hepatic Adverse Effect. Chin. Med. 2021, 16, 1–17.
10. Nazarudin, A.A.; Zulkarnain, N.; Hussain, A.; Mokri, S.S.; Nordin, I.N.A.M. Review on Automated Follicle Identification for Polycystic Ovarian Syndrome. Bull. Electr. Eng. Inform. 2020, 9, 588–593.
11. Kalyani, C.; Ramudu, K.; Reddy, G.R. Enhancement and Segmentation of Medical Images Using AGCWD and ORACM. Int. J. Online Biomed. Eng. 2020, 16, 45–56.
12. Nazarudin, A.A.; Zulkarnain, N.; Mokri, S.S.; Zaki, W.M.D.W.; Hussain, A. An Implementation of Otsu Thresholding and the Chan-Vese Method on the PCO Segmentation of Ultrasound Images. In Proceedings of the 2020 2nd International Conference on Electrical, Control and Instrumentation Engineering (ICECIE), Kuala Lumpur, Malaysia, 28 November 2020
13. Mamdouh, R.; El-Khamisy, N.; Amer, K.; Riad, A.; El-Bakry, H.M. A New Model for Image Segmentation Based on Deep Learning. Int. J. Online Biomed. Eng. 2021, 17, 28–47.
14. Azli, S.N.B.B.; Azli, M.; Zulkarnain, N.; Nazarudin, A.A.; Mokri, S.S.; Ahmad, M.F. Ultrasound Image Segmentation Using a Combination of Edge Enhancement and Kirsch's Template Method for Detecting Follicles in Ovaries. In Proceedings of the International Conference on Industrial Engineering and Operations Management, Istanbul, Turkey, 7–10 March 2022; IEOM Society International: Southfield, MI, USA; pp. 1842–1857.
15. Ameer, S.F.; Nayyef, Z.T.; Fahad, Z.H.; AlRubee, I.R.N. Using Morphological Operation and Watershed Techniques for Breast Cancer Detection. Int. J. Online Biomed. Eng. 2020, 16, 140–149.
16. Noorfizir, A.; Rachmatullah, M.N.; Sulong, G. Hybrid Multilevel Thresholding-Otsu and Morphology Operation for Retinal Blood Vessel Segmentation. Eng. Lett. 2020, 28, 180–191.
17. Srinivas, Kachibhotla and Phani Kumar, Ch. Raghavendra. 'An Improvised Follicle Polycystic Ovarian Detection Using AKF from a Sequence of Given Ultrasound Images'. 1 Jan. 2022 : 7717 – 7732.
18. L. E. Kenigsberg, C. Agarwal, S. Sin et al., "Clinical utility of magnetic resonance imaging and ultrasonography for diagnosis of polycystic ovary syndrome in adolescent girls," Fertility and Sterility, vol. 104, no. 5, pp. 1302–1309, 2015.
19. The Rotterdam Eshre/Asrm-sponsored Pcos consensus workshop group, "Revised 2003 consensus on diagnostic criteria and long-term health risks related to polycystic ovary syndrome (PCOS)," Human Reproduction, vol. 19, no. 1, pp. 41–47, 2004.
20. A. Denny, A. Raj, A. Ashok, C. M. Ram, R. George, and I. Hope, "Detection and prediction system for polycystic ovary syndrome (PCOS) using machine learning techniques," IEEE Region 10 Annual International Conference, Proceedings/TENCON, vol. 2019, Article ID 8929674, 678 pages, 2019.
21. Vishwakarma, S., Goswami, R. S., Nayudu, P. P., Sekhar, K. R., Arnepalli, P. R., Thatikonda, R., & Abdel-Rehim, W. M. (2023). Secure Federated Learning Architecture for fuzzy classifier in healthcare environment. Soft Computing. https://doi.org/10.1007/s00500-023-08629-4 - (Publisher: Springer Link)
22. Yendluri, D. K., Ponnala, J., Tatikonda, R., Kempanna, M., Thatikonda, R., & Bhuvanesh, A. (2023). Role of RPA & AI in Optimizing Network Field Services. *2023 7th International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS)*. **https://doi.org/10.1109/csitss60515.2023.10334117(IEEE)**
23. Thatikonda, R., Satpathy, S., Ali, S., Trivedi, M. C., & Choudhry, M. (2023). Towards computationally efficient and real-time distracted driver detection using Convolutional Neutral Networks. *Artificial Intelligence, Blockchain, Computing and Security Volume 1*, 37–46. **https://doi.org/10.1201/9781003393580-7**
24. Thatikonda, R., Dash, B., Ansari, M. F., & Vaddadi, S. A. (2023). E-business trends and challenges in the Modern Digital Enterprises in Asia. *Digital Natives as a Disruptive Force in Asian Businesses and Societies*, 22–43. https://doi.org/10.4018/978-1-6684-6782-4.ch002 **(In book: Digital Natives as a Disruptive Force in Asian Businesses and Societies Publisher: IGI Global)**
25. Naga Simhadri, TNVR Swamy, Awareness among teaching on Artificial Intelligence (AI) and Machine learning (ML) applications based on fuzzy in education sector at USA, Soft Computing, Pages 1-9, 2023.
26. N Simhadri Apparao Polireddi, J Kavitha, Effectiveness of automated chatbots for operational

support and self-service based on fuzzy classifier for ASD, Soft Computing, Pages 1-8. 2023.

27. Naga Simhadri Apparao Polireddi, K Chaitanya, Web accessibility evaluation of private and government websites for people with disabilities through fuzzy classifier in the USA, Soft Computing, Pages 1-9. 2023.
28. R Pulimamidi, GP Buddha, Applications of Artificial Intelligence Based Technologies in The Healthcare Industry, Tuijin Jishu/Journal of Propulsion Technology 44 (3), 4513-4519.
29. R Pulimamidi, GP Buddha, AI-Enabled Health Systems: Transforming Personalized Medicine And Wellness, Tuijin Jishu/Journal of Propulsion Technology 44 (3), 4520-4526.
30. R Pulimamidi, P Ravichandran, Connected Health: Revolutionizing Patient Care Through Artificial Intelligence Innovations, Tuijin Jishu/Journal of Propulsion Technology 44 (3), 3940-3947.
31. Ramya Manikyam, J. Todd McDonald, William R. Mahoney, Todd R. Andel, and Samuel H. Russ. 2016.Comparing the effectiveness of commercial obfuscators against MATE attacks. In Proceedings of the 6th Workshop on Software Security, Protection, and Reverse Engineering (SSPREW'16)
32. R. Manikyam. 2019.Program protection using software based hardware abstraction.Ph.D. Dissertation.University of South Alabama