ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/366320486

Comparative Analysis of Artificial Intelligence in the Diagnosis of Polycystic Ovary Syndrome

Preprint · December 2022

DOI: 10.13140/RG.2.2.27068.31360

CITATIONS
0

READS
103

2 authors, including:

David Anda
Bournemouth University

1 PUBLICATION **0** CITATIONS

SEE PROFILE

All content following this page was uploaded by David Anda on 16 December 2022.

The user has requested enhancement of the downloaded file.

Comparative Analysis of Artificial Intelligence in the Diagnosis of Polycystic Ovary Syndrome

David Anda
Department of Computing and Informatics
Bournemouth University
Bournemouth, United Kingdom
s5437545@bournemouth.ac.uk

Eddie Iyamah
Department of Computing and Informatics
Bournemouth University
Bournemouth, United Kingdom
s5441858@bournemouth.ac.uk

***Abstract*— Polycystic ovary syndrome (PCOS) is a complex health condition that affects the ovaries of women of childbearing age and can lead to irregular ovulation and infertility. Its symptoms are nonspecific and may vary from person to person, making it difficult to diagnose. The application of artificial intelligence to various forms of healthcare data offers the possibility of providing more accurate diagnoses and better treatment outcomes for patients with PCOS. This paper explores existing research in the diagnosis of PCOS and compares various, methodologies, dataset structures, feature selection techniques and the performance evaluation of machine learning models such as Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Tree (DT), K-Nearest Neighbors (KNN) in diagnosing PCOS. We identify CNN as the best-performing model despite the current challenges involved, reiterate the importance of AI in improving healthcare delivery and conclude by suggesting current limitations, the various factors that influence model performance and future recommendations that may further enhance the diagnosis of PCOS.**

Keywords—Polycystic ovary syndrome, artificial intelligence, diagnosis, feature selection, performance evaluation

I. INTRODUCTION

Polycystic Ovary Syndrome (PCOS) is a common medical condition with a set of symptoms that affects girls and women of reproductive age. Some of these symptoms are changes in the menstrual cycle, abnormal facial and body hair growth, acne, obesity, presence of cysts in the ovaries and infertility. It is a complex, uncurable condition attributed to the imbalance of reproductive hormones that generally affect how the ovaries work. Women with PCOS are at a high risk of developing other health problems like type 2 diabetes, gestational diabetes (high blood sugar during pregnancy), high cholesterol levels, high blood pressure, sleep apnea and stroke in the future [1] Research has shown that the general prevalence of PCOS in an unspecified population is 3-10% [2]. Fig. 1 shows the differences between a normal ovary and a Polycystic ovary.

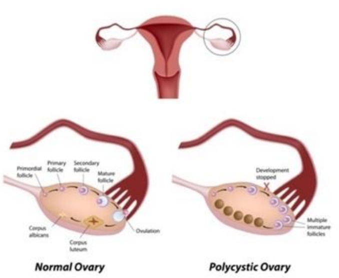

Fig. 1. Difference between Polycystic ovary and normal ovary [1]

Despite the potential severity of this syndrome and its growing prevalence, clinicians have found it difficult to detect as the exact cause is not known and some people with PCOS do not show any symptoms. It is important to consider a woman's family history, androgen levels, weight and insulin resistance when diagnosing PCOS. Additionally, not everyone with PCOS has ovarian cysts, and not everyone with ovarian cysts has PCOS, which makes the diagnosis more difficult and eliminates the possibility of relying exclusively on ultrasound results [3]. The severity and presentation of PCOS have been reported to vary according to the race and age of women. Adolescents with PCOS can be misdiagnosed or completely undiagnosed as some of these symptoms such as cyst development, acne, and hormonal fluctuations can also be present during puberty years. Studies have also shown that women of colour are at a higher risk of PCOS and suffer more severely than white women [4] because they have higher insulin resistance and high mortality from heart disease and diabetes. These varying symptoms and presentations for different women make the diagnosis of PCOS even harder for clinicians and often require more than one assessment with different clinicians. A widely used criterion by medical professionals and researchers which is based on a consensus among experts is the Rotterdam Criteria [5], which states that if a woman has at least two of the following symptoms she should be diagnosed with PCOS: irregular periods (more than 40 days or no periods), clinical signs or blood tests showing high levels of androgen and the appearance of ovarian cysts on an ultrasound. PCOS is typically diagnosed by one or a combination of these symptoms, but diagnosis remains difficult because these are expert-derived criteria and not evidence-based treatment recommendations. Tests or experiments that can be conducted universally and accurately to determine a patient's condition are still lacking. These challenges associated with this syndrome have led to various studies on the experiences of women regarding their clinical assessments and diagnosis of PCOS. Tests or experiments that can be conducted universally and accurately to determine a patient's condition are still lacking. These challenges associated with this syndrome have led to various studies on the experiences of women regarding their clinical assessments and diagnosis of PCOS. A previous survey by [6] carried out in Australia reported that PCOS diagnosis takes a long time, involves many medical professionals and left most women with unanswered questions. Another survey [7] carried out on 1385 women aged 18 to 35 years living mainly in North America reported that 33.6% of them got their PCOS diagnosis after 2 years, and about 50% of them had to visit more than 3 health professionals before arriving at a diagnosis. Most women are unhappy with the circumstances surrounding the diagnosis, so they self-diagnose and seek treatment independently.

XXX-X-XXXX-XXXX-X/XX/$XX.00 ©20XX IEEE

These gaps in diagnosing PCOS, have led to research and various implementations of technology and the use of Artificial Intelligence (AI) to build diagnostic models to overcome the issues of accurately and efficiently identifying PCOS. Artificial intelligence is a broad term that describes the science that enables computer programmes to mimic and better comprehend human intellect. In simpler terms, AI aims to imitate human thinking and deduce conclusions from existing knowledge at scale. The use of AI coupled with the increasing availability and access to healthcare data is currently transforming the delivery of healthcare, with recent advancements and applications proving successful in assisting physicians to improve diagnoses, identify treatments, boost patient engagement, and streamline administrative tasks [8].

This research would explore relevant works of literature and current applications using relevant data features and machine learning algorithms in the diagnosis of PCOS. Section II will outline various popular machine learning techniques employed in the reviewed works of literature, such as K-Nearest Neighbour (KNN), Decision Tree Classifier (DT), Support Vector Machine (SVM), Logistic Regression (LR) and deep learning techniques like artificial neural networks (ANN) and Convolutional neural networks (CNN) and would evaluate their performances towards the early diagnosis of PCOS. Section III provides an overall comparison between the various evaluated machine learning models in their efficiency in diagnosing PCOS. The authors' concluding remarks and recommendations are provided in section IV.

II. MACHINE LEARNING ALGORITHMS

A. *Artificial Neural Networks (ANNs)*

Artificial Neural Networks (ANNs) which are inspired by the interconnected neural network of the nerve cells of the human brain include artificial neurons that mimic the process of the biological central nervous system [9]. During network training, weights are modified and adjusted to form the structure of ANNs. Additionally, weights will be recalculated by taking into account the differences between the actual class labels and the expected output labels when the output is determined based on the class labels. There are many types and classes of ANNs including Feed Forward Neural Networks, Convolutional Neural Networks (CNNs), and Recursive Neural Networks (RNNs).

A large amount of research has been done to detect PCOS using deep learning algorithms, such as CNNs and RNNs. Ahmetasevic et al. [10] developed an expert system using an Artificial Neural Network to classify instances of PCOS from a dataset containing 1000 samples distributed in two categories: healthy subjects and subjects with disease. Fig. 2 shows the ANN architecture of the expert system. The dataset contains several attributes which are proven to be contributors to the development of PCOS. Attributes such as the number of follicles, free testosterone, free androgen index and oligoovulation are fed as inputs in the ANN.

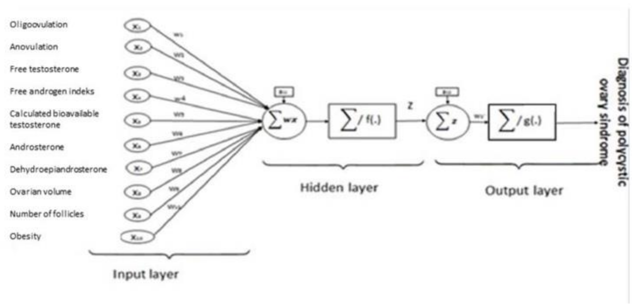

Fig. 2. Architecture of expert system [10]

The authors employed the Levenberg-Marquardt algorithm in building the ANN to adjust the parameters of the network and to improve the overall performance of the model. The performance of the model was evaluated based on three main criteria: sensitivity, specificity and accuracy mathematically expressed in equations 1-3 respectively.

$$sensitivity = \frac{TP}{(TN+FN)} \quad (1)$$

$$specificity = \frac{TN}{(TN+FP)} \quad (2)$$

$$accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)} \quad (3)$$

TP – true positive TN – true negative

FP – false positive FN – false negative

The sensitivity, specificity and accuracy of the model are 96.8%, 90% and 96.1% respectively, indicating the model's high performance in pattern recognition of PCOS.

Sumathi et al [11] built a Convolutional Neural Network (CNN) model to classify cysts and effectively diagnose PCOS from ovarian ultrasound images. CNN is a deep learning architecture that also takes inspiration from biological processes. It takes inspiration from the natural visual perception mechanism of living creatures [12]. The deep learning architecture can obtain effective representations of the input image which enables it to describe patterns directly from pixels. The classification study involved pre-processing the ultrasound images to remove speckle noise as it can affect the accuracy of the model, segmenting the region of interest (cysts) using a watershed algorithm and extracting features using the OpenCV module which is used for measuring physical parameters like area, perimeter, extent, orientation and solidity. The extracted features serve as the input for training the CNN model. After training the model and validating it with the ovarian ultrasound images, they reported a performance accuracy of 85%. Fig. 3 shows the segmentation process of the cysts from the ultrasound images using the watershed algorithm.

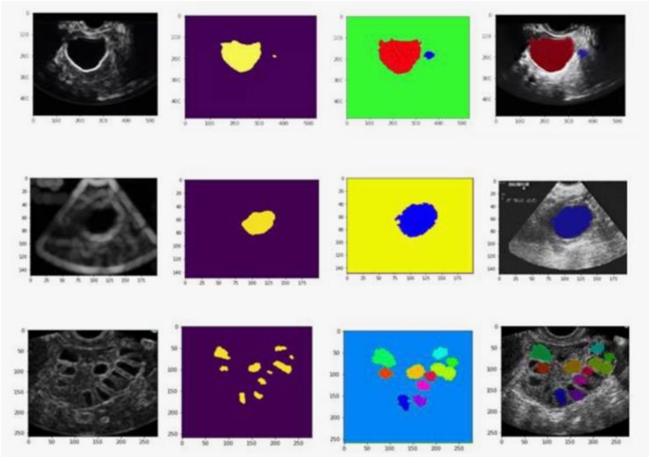

Fig. 3. Segmentation process of the cysts [11]

Similarly, Bharati et al. [1] compared the performance of a lightweight Convolutional Neural Network (CNN) (PCONet) and a fine-tuned 45-layered InceptionV3 CNN in detecting PCOS from ovarian ultrasound images. To prevent bias, there were two independent datasets used in this experiment. One of which was split and used for the traditional approach of training and validating both models while the other was used as a final independent test set. A total of 1694 identical images were used in the initial training and validation of both models, of which 1364 were used for training and 384 for validation. The test set contained 154 healthy ovarian images and 185 ovarian images where cysts were present. Input images for both models were resized to 224 x 224 pixels, normalised to improve convergence during model training and augmented to add variety to the dataset. The PCONet network consisted of five convolution blocks that each contained a convolutional layer and a 2x2 max pool layer, a 3x3 kernel size for each convolutional layer, a rectified linear activation function (ReLU), the Adam optimizer, binary cross-entropy loss function and a Sigmoid activation function in the output layer. The default Inception V3 model which had an output layer with a 1x1x1000 dimension was modified to replace its top layers with two dense layers and an output layer that consisted of two neurons which represented the binary classification of this dataset. The ReLU activation function, Adam optimizer and binary cross-entropy loss were also used in this model with a learning rate of 0.00001. Fig. 4 and Fig. 5 show the network structure of this model and the first convolution block of PCONet respectively. After training, validating and testing both models using both datasets, PCONet had a classification accuracy of 98.12% and the fine-tuned Inception V3 was 96.56% accurate. PCONet was also more precise in detecting PCOS with a precision score of 96% compared to 94% of Inception V3. InceptionV3, however, had a higher recall score when detecting PCOS-infected ovaries than PCONet, which was 100% to 97%. Overall, the developed PCONet model which has less depth and is computationally more efficient than the inceptionV3 model performed better and is proposed as a solution to assist in the early detection of PCOS from ultrasound images.

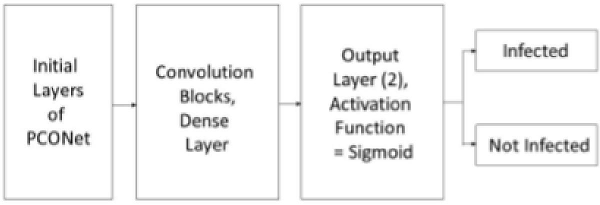

Fig. 4. Network structure of PCONet [1]

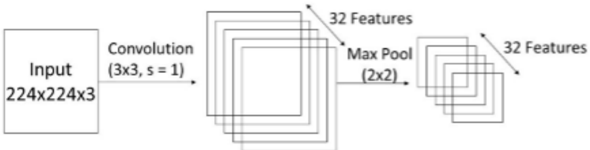

Fig. 5. Convolution block of PCONet [1]

B. Support Vector Machines (SVM)

Support Vector Machine (SVM) is a machine learning algorithm for classification and regression tasks that is built on kernels. SVM has been used as a powerful tool for handling real-world binary classification problems due to its exceptional generalisation capability, optimum solution, and discriminative power [13].

Wang et al. [14] proposed a non-invasive method and investigated the predictive capability of a multi-layer perceptron classifier (MLP), eXtreme gradient boosting classifier (XGBoost), and SVM in the diagnosis of PCOS using tongue images and pulse parameters. 486 Chinese women aged between 20 to 44 were used for this study with 201 of them being without PCOS and 285 of them diagnosed with PCOS using the 2003 Rotterdam criteria. They used the Propensity score matching (PSM) method to create age-based control groups and minimise the impact of selection bias. Feature selection was done using Lasso Regression techniques to avoid the impact of overfitting ad multicollinearity between tongue and pulse features. They implemented a 10-fold resampling technique method with a holdout of 80% for the training set and the test set accounted for 20%. Accuracy, Sensitivity, Specificity, AUC (Area Under the Curve) ROC (Receiver Operating Characteristics) curve – a graph that displays the model's performance at various classification threshold settings, and Decision curve analysis (DCA) were the evaluation metrics of choice to evaluate all three models. All three models reported high predictive capabilities with AUCs above 0.9. The SVM model had the highest accuracy of 94% compared to XGBoost and MLP which were 75% and 90% respectively. Some of the features that were most significantly related to the presence of PCOS in women were the colours of the tongue body and coating (those of women diagnosed with PCOS were darker), women without PCOS had moister tongues and the front of their tongues are generally reddish compared to those diagnosed with PCOS etc. Overall, the SVM model was the best classifier in this study after comparing its predictive capability and clinical utility using various evaluation criteria.

Another study involving the use of ovarian ultrasound images was carried out by Purnama et al. [15]. The authors used preprocessing and feature extraction techniques to speed up the detection of PCO follicles and subsequently the diagnosis of PCOS using verified grayscale ultrasound images. 60 normal ovary images and 20 ovaries with PCO follicles were used and they went through several preprocessing stages such as noise filtering, contrast enhancement and inverted negative transformation and binarization to distinctly identify the presence of PCO follicles. Segmentation was applied using the edge canny method to easily differentiate the background from the desired follicles for further analysis. Fig. 6 shows the block diagram of the preprocessing technique employed and Fig. 7 shows an ovarian ultrasound image before and after preprocessing. Identified follicles were cropped into bounding boxes as separate new images to extract their features. Gabor wavelet – a linear filter used for texture analysis was used for feature extraction and was configured to only extract feature vectors that represented PCO and non-PCO follicles. The dataset was split into two using 2 groups of texture features based on: (1). Mean, and (2.) Mean, Entropy, Kurtosis, Skewness, and Variance. One dataset (Dataset A) consisted of 40 images, 26 of them being normal, 14 classified as PCOS images and segmented 275 follicle images. The second dataset (Dataset B) consisted of 34 normal images, 6 PCOS images and 339 segmented follicle images. For classification and model training and classification of PCO and non-PCO follicles using feature vectors, Neural Network-Learning Vector Quantization (NN-LVQ). SVM and KNN were implemented. NN-LVQ was trained on both datasets with different numbers of hidden neurons (HN) (32, 256, 512 and 1024), learning rates (LR) (0.01 and 0.5) and iterations (100, 300, 500 and 1000). When using 1024 HN, a learning rate of 0.01 and after 1000 iterations, dataset A and dataset B recorded their highest accuracies of 72.36% and 74.63 respectively. Due to non-linearity in both datasets, the researchers used the RBF Kernel and Polynomial Kernel, as well as different folds of the C parameter ranging from 10 to 200 to discover the best hyperplane that splits the target classes. SVM showed that fewer texture characteristics/feature vectors may produce more accurate results with dataset A reaching an accuracy of 82.55% compared to 78.17% for dataset B. Using the KNN model with an emphasis on measuring the Euclidean distance between data points to determine what class they belonged to. Dataset A yielded a higher accuracy of 80.73% compared to 78.81% from dataset B. This finding also supports the argument that fewer feature vectors might yield better results for the classification of PCO follicles. In conclusion, the SVM model with an RBF Kernel using fewer texture features was their proposed solution for early PCOS diagnosis using ultrasound images.

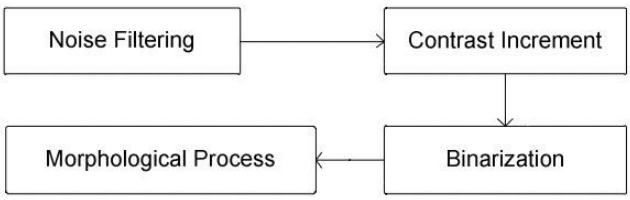

Fig. 6. Block diagram of the preprocessing technique [15]

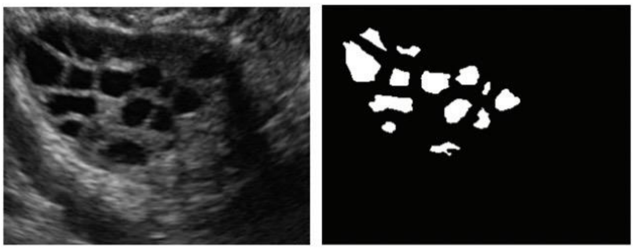

Fig. 7. ovarian ultrasound image before and after preprocessing [15]

In yet another study involving the use of SVM in PCOS diagnosis, Abu Adla et al. [16] worked in tandem with physicians to decide what features most impact the diagnosis of PCOS and what evaluation metric to use during the model training and evaluation phases. 541 women were included in the study and were collected from 10 hospitals in India with 39 features including ultrasonic image parameters, physical features, and hormonal variables. Using the Analysis of Variance (ANOVA) test to find relationships between features (LINK) and a discussion with an obstetrician-gynaecologist, they computed scores and aligned them with current medical criteria to identify the most significant features in diagnosing PCOS. Features relating to blood pressure were deemed insignificant and removed from the dataset. To prevent the harmful effects of misdiagnosis, precision - which measures a model's ability to accurately classify patients with PCOS - was the evaluation metric of choice. To further reduce feature dimensions and improve computational time, they used a Sequential Feature Selection method to gradually iterate over features and identify those that significantly improved the precision of 11 classifier models. Among the top-performing models were KNN, Linear SVM, and Polynomial SVM, however, to propose an optimal solution model, they considered model accuracy and sensitivity and used a 10-Fold Cross Validation (CV) resampling technique to avoid the effects of bias when holding out data in classification problems. With an accuracy of 91.6%, a precision of 93.66%, and a sensitivity of 80.6%, the Linear SVM model was the proposed model for diagnosing PCOS and weight gain, hair loss, acne, age, pulse rate, the thickness of the endometrium and exercise frequency were some of the most contributing factors.

C. K-nearest neighbor (KNN)

K-nearest neighbor (KNN) is a well-known classification algorithm which has drawn more attention from researchers in machine learning because of its simplicity, effectiveness and pattern recognition [17]. When training a dataset, KNN uses instance-based learning to compare newly created instances to instances already stored in memory. The accuracy of the model depends on two factors: the value of k and the number of features.

Tanwani [18] built a KNN and Logistic Regression (LR) models to effectively diagnose PCOS from a dataset comprising of 540 samples and 43 attributes (features). The Filter method was used to perform feature selection with the best 15 features ranked. The features are then fed as input into the LR model and KNN model. The performances of each model are compared to ascertain the best-supervised learning algorithm for effectively diagnosing PCOS. Fig. 8 shows the accuracy of the KNN model is highest when the value of k is 5. Fig. 9 shows that out of the 15 features ranked, 9 or 19 are needed to give maximum accuracy while Fig. 10 shows that

10 or 36 features give maximum accuracy for the LR model. Due to computational costs, only 9 and 10 were selected for prediction for the KNN and LR models respectively. The performance metrics showed that the KNN model yielded an F1 score of 91% after the prediction, while the LR model yielded an F1 score of 92% accuracy. The F1-score is a measure of a model's accuracy on a dataset and is commonly used to evaluate the performance of binary classification models. Although the LR algorithm outperformed the KNN model, the KNN model still proves to be a good linear classifier.

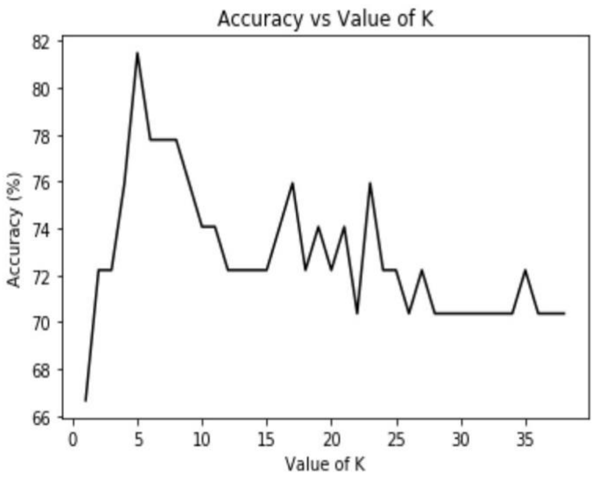

Fig. 8. Accuracy vs k [18]

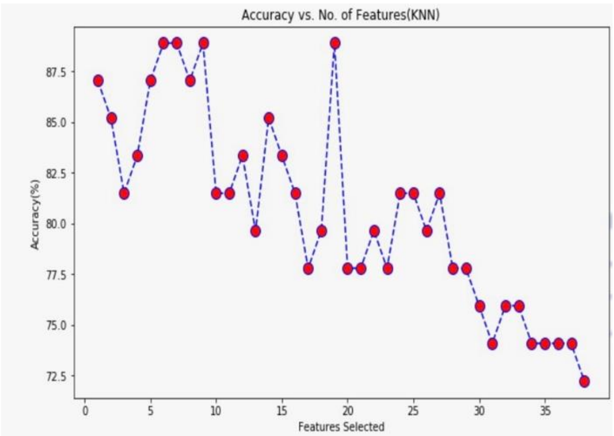

Fig. 9. Accuracy vs. No. of Features (KNN) [18]

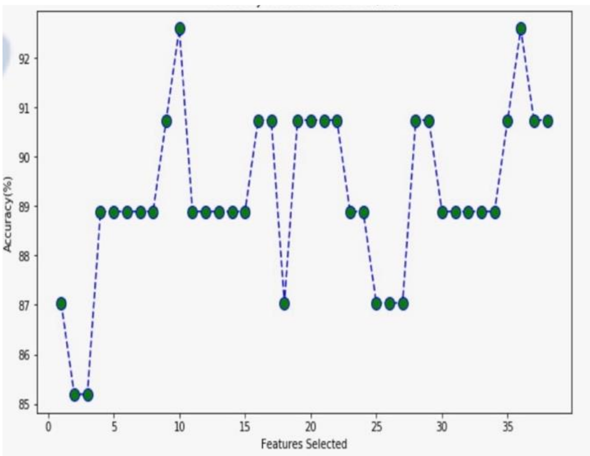

Fig. 10. Accuracy vs. No. of Features (LR) [18]

D. Decision Tree classifier

A decision tree is a tree-based method in which each route leading from the root is characterised by a data-separating sequence up until a Boolean result is reached at the leaf node [19]. It is one of the most popular classification techniques used in machine learning with more researchers employing the techniques in various fields such as medical diagnosis.

Chauhan et al. [20] developed a mobile application and proposed the Decision Tree Classifier – a simple rule-based machine learning classifier that splits dataset features into isolated classes using conditional yes/no questions as the most accurate model for the early diagnosis of PCOS. In their research, they created questionnaires asking 267 women in rural and urban areas in India if they had been diagnosed with PCOS or not, and if they had experienced symptoms like unusual hair growth, acne, rapid weight gain or loss, period lengths, irregular/missed periods, hair thinning, cycle lengths, difficulty conceiving, frequency of exercising, feelings of tiredness, mood swings, eating habits and their age from a range of age group categories. Their dataset was normally distributed across region classifications (rural & urban), age and lifestyle attributes. Overall, 61 women stated they had been diagnosed with PCOS while 206 had never been diagnosed. K-Nearest Neighbours (KNN), Naive Bayes, Support Vector Machine (SVM), Decision Tree, and Logistic regression were the 5 models that were trained on their dataset and their performances were evaluated using the total number of correctly classified labels in the evaluation phase (accuracy) as the baseline metric in determining the overall model suitability in the early detection of PCOS. The Decision Tree Classifier produced the best result boasting an accuracy of 81% with obesity, exercise levels, irregular periods, period length, dark patches and age group being the determinant features.

III. COMPARISON

This section gives a summary of the performances of the machine learning models employed in the reviewed works of literature. The various models are compared to ascertain the best-performing machine learning technique in detecting Polycystic ovary syndrome. Table 1 shows the various reviewed literature as well as the methodologies employed and the model's accuracy.

TABLE I.

Reference	**Methodology**	**Model**	**Accuracy (%)**
Ahmetasevic et al. [10]	Developed an ANN system with Levenberg-Marquardt algorithm to diagnose PCOS	ANN	96.1
Sumathi et al. [11]	Built a Convolutional Neural Network (CNN) model to classify cysts and diagnose PCOS from ovarian ultrasound images	CNN	85

Bharati et al. [1]	Built and compared a lightweight Convolutional Neural Network (CNN) (PCONet) and a fine-tuned 45-layered InceptionV3 CNN in detecting PCOS from ovarian ultrasound images	CNN	98.12
Weiying Wang et al. [14]	Comparing the capabilities of SVM model to MLP and XGBoost in the diagnosis of PCOS using tongue images and pulse parameters	SVM	94
Purnama et al. [15]	Performed preprocessing and feature extraction techniques to speed up the detection of PCO follicles and subsequently the diagnosis of PCOS using verified grayscale ovarian ultrasound images	SVM	82.55
Abu Adla et al. [16]	Built an automated system for detecting PCOS	SVM	91.6
Tanwani [18]	Built a KNN and Logistic Regression (LR) models to effectively diagnose PCOS	KNN	91
Chauhan et al. [20]	Developed a mobile application and proposed the Decision Tree Classifier (DT)	DT	81

Upon comparison, the authors who employed Neural Networks in their study, after evaluation, proposed the best-performing models in the early detection of PCOS. Bharati et al. [1] reported an accuracy of 98.12% using a developed lightweight CNN model to classify ovarian ultrasound images. CNNs have proven to be the most effective classification algorithm for chronic disease detection despite the challenges involved in training CNN models such as the availability of large datasets and heavy computational costs CNN models exhibit good performance accuracy [21].

IV. CONCLUSION

Digitized healthcare and AI subfields like machine learning and deep learning are rapidly transforming medical delivery by facilitating the diagnosis of diseases, drug discovery, identification of patient risk, and development of techniques to manage treatment [22]. Effectively diagnosing diseases is crucial in ensuring patients' well-being and prescribing medication to manage and improve their condition. Human error and lack of well-defined diagnostic tests can lead to misdiagnosis and inefficiency in providing optimal care to patients which can lead to waste of resources or more complex issues like worsened health conditions and death. AI techniques and various machine learning models have shown promising signs in assisting clinical decisions, diagnosis and treatment of diseases. However, some advancements can be made through the provision of more medical data, accurate selection of features and evaluation model performance We carried out a study on five major machine learning algorithms used in diagnosing Polycystic Ovary Syndrome (PCOS) namely Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Support Vector Machine (SVM), *K*-nearest neighbors (KNN), Decision Tree classifier (DT) and it was found that the CNN models proved to be the best performing algorithm for effectively diagnosing PCOS. Although the CNN models performed well, there are a lot of factors that contribute to the success of any classification algorithm. Performing hyper-parameter tuning or utilising optimisation algorithms to improve the overall performance of the model, nature and size of the dataset and feature selection techniques employed. From other studies, utilising an ensemble machine learning algorithm (a combination of more than one machine learning technique) can help to effectively classify data with maximum accuracy. An in-depth analysis of these AI methods helps researchers ascertain the best ways to in PCOS diagnosis and explore more ways to improve them.

REFERENCES

[1] 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.

[2] W. M. Wolf, R. A. Wattick, O. N. Kinkade, and M. D. Olfert, 'Geographical prevalence of polycystic ovary syndrome as determined by region and race/ethnicity', *International Journal of Environmental Research and Public Health*, vol. 15, no. 11. MDPI AG, Nov. 20, 2018. doi: 10.3390/ijerph15112589.

[3] K. M. Hoeger, A. Dokras, and T. Piltonen, 'Update on PCOS: Consequences, Challenges, and Guiding Treatment', *Journal of Clinical Endocrinology and Metabolism*, vol. 106, no. 3. Endocrine Society, pp. E1071–E1083, Mar. 01, 2021. doi: 10.1210/clinem/dgaa839.

[4] L. Engmann *et al.*, 'Racial and ethnic differences in the polycystic ovary syndrome metabolic phenotype', in *American Journal of Obstetrics and Gynecology*, May 2017, vol. 216, no. 5, pp. 493.e1-493.e13. doi: 10.1016/j.ajog.2017.01.003.

[5] R. Wang and B. W. J. Mol, 'The Rotterdam criteria for polycystic ovary syndrome: Evidence-based criteria?', *Human Reproduction*, vol. 32, no. 2, pp. 261–264, Feb. 2017, doi: 10.1093/humrep/dew287.

[6] M. E. Gibson-Helm, I. M. Lucas, J. A. Boyle, and H. J. Teedea, 'Women's experiences of polycystic ovary syndrome diagnosis', *Fam Pract*, vol. 31, no. 5, pp. 545–549, Oct. 2014, doi: 10.1093/fampra/cmu028.

[7] M. Gibson-Helm, H. Teede, A. Dunaif, and A. Dokras, 'Delayed diagnosis and a lack of information associated with dissatisfaction in women with polycystic ovary syndrome', *Journal of Clinical Endocrinology and Metabolism*, vol. 102, no. 2. Endocrine Society, pp. 604–612, Feb. 01, 2017. doi: 10.1210/jc.2016-2963.

[8] S. E. Dilsizian and E. L. Siegel, 'Artificial intelligence in medicine and cardiac imaging: Harnessing big data and advanced computing to provide personalized medical diagnosis and treatment', *Curr Cardiol Rep*, vol. 16, no. 1, Jan. 2014, doi: 10.1007/s11886-013-0441-8.

[9] H. Danaei Mehr and H. Polat, 'Diagnosis of polycystic ovary syndrome through different machine learning and feature selection techniques', *Health Technol (Berl)*, vol. 12, no. 1, pp. 137–150, Jan. 2022, doi: 10.1007/s12553-021-00613-y.

[10] A. Ahmetasevic, L. Alicelebic, B. Bajric, E. Becic, A. Smajovic, and A. Deumic, 'Using Artificial Neural Network in Diagnosis of Polycystic Ovary Syndrome', in *2022 11th Mediterranean Conference on Embedded Computing, MECO 2022*, 2022. doi: 10.1109/MECO55406.2022.9797204.

[11] M. Sumathi, P. Chitra, R. Sakthi Prabha, and K. Srilatha, 'Study and detection of PCOS related diseases using CNN', *IOP Conf Ser Mater Sci Eng*, vol. 1070, p. 012062, Feb. 2021, doi: 10.1088/1757-899x/1070/1/012062.

[12] J. Gu *et al.*, 'Recent advances in convolutional neural networks', *Pattern Recognit*, vol. 77, pp. 354–377, May 2018, doi: 10.1016/j.patcog.2017.10.013.

[13] J. Cervantes, F. Garcia-Lamont, L. Rodríguez-Mazahua, and A. Lopez, 'A comprehensive survey on support vector machine classification: Applications, challenges and trends', *Neurocomputing*, vol. 408, pp. 189–215, Sep. 2020, doi: 10.1016/j.neucom.2019.10.118.

[14] W. Wang *et al.*, 'Machine Learning Prediction Models for Diagnosing Polycystic Ovary Syndrome Based on Data of Tongue and Pulse', *SSRN Electronic Journal*, 2022, doi: 10.2139/ssrn.4095191.

[15] B. Purnama, U. N. Wisesti, Adiwijaya, F. Nhita, A. Gayatri, and T. Mutiah, 'A classification of polycystic Ovary Syndrome based on follicle detection of ultrasound images', in *2015 3rd International Conference on Information and Communication Technology, ICoICT 2015*, Aug. 2015, pp. 396–401. doi: 10.1109/ICoICT.2015.7231458.

[16] Y. A. Abu Adla, D. G. Raydan, M. Z. J. Charaf, R. A. Saad, J. Nasreddine, and M. O. Diab, 'Automated Detection of Polycystic Ovary Syndrome Using Machine Learning Techniques', in *International Conference on Advances in Biomedical Engineering, ICABME*, 2021, vol. 2021-October, pp. 208–212. doi: 10.1109/ICABME53305.2021.9604905.

[17] J. Gou, H. Ma, W. Ou, S. Zeng, Y. Rao, and H. Yang, 'A generalized mean distance-based k-nearest neighbor classifier', *Expert Syst Appl*, vol. 115, pp. 356–372, Jan. 2019, doi: 10.1016/j.eswa.2018.08.021.

[18] N. Tanwani, 'Detecting PCOS using Machine Learning', *International Journal of Modern Trends in Engineering and Science*, vol. 7, no. 1, pp. 1–20, 2020, doi: 10.13140/RG.2.2.10265.24169.

[19] B. Charbuty and A. Abdulazeez, 'Classification Based on Decision Tree Algorithm for Machine Learning', *Journal of Applied Science and Technology Trends*, vol. 2, no. 01, pp. 20–28, Mar. 2021, doi: 10.38094/jastt20165.

[20] P. Chauhan, P. Patil, N. Rane, P. Raundale, and H. Kanakia, 'Comparative Analysis of Machine Learning Algorithms for Prediction of PCOS', in *2021 International Conference on Communication information and Computing Technology (ICCICT)*, Jun. 2021, pp. 1–7. doi: 10.1109/ICCICT50803.2021.9510128.

[21] S. Kugunavar and C. J. Prabhakar, 'Convolutional neural networks for the diagnosis and prognosis of the coronavirus disease pandemic', *Vis Comput Ind Biomed Art*, vol. 4, no. 1, p. 12, Dec. 2021, doi: 10.1186/s42492-021-00078-w.

[22] Y. Kumar, A. Koul, R. Singla, and M. F. Ijaz, 'Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda', *J Ambient Intell Humaniz Comput*, Jan. 2022, doi: 10.1007/s12652-021-03612-z.

View publication stats