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Deep Learning Enhanced Predictive Models for Early Detection and Clinical Risk Stratification of PCOS and PCOD in Womens Health Diagnostics

Ms. Hema prasanna.S,
Assistant professor
Department of Information Technology
Sathyabama Institute of Science and Technology, Chennai, India
hemaprasanna.s.it@sathyabama.ac.in

Sweety Joyce.A,
UG Student
Department of Information Technology
Sathyabama Institute of Science and Technology, Chennai, India
sweetyjoyce14@gmail.com

Pooja.S,
UG Student
Department of Information Technology
Sathyabama Institute of Science and Technology, Chennai, India
poojasubash491@gmail.com

Ms. L. Mary Gladence,
Professor
Department of Information Technology
Sathyabama Institute of Science and Technology
Chennai, India Marygladence.it@sathyabama.ac.in

Abstract—**Polycystic Ovary Syndrome (PCOS) and Polycystic Ovarian Disease (PCOD) have emerged as two of the most prevalent hormonal disorders experienced by the female population across the community of reproductive age. These diseases have also been associated with other prevalent health conditions like infertility, metabolic problems, and psychological problems. Hence, the detection of these diseases has assumed immense significance, as timely detection of the diseases along with the accurate estimation of the associated health risks is considered to be the key to the delivery of the best possible treatment to the patients. In this context, this particular paper has proposed the framework of the application of the associated machine learning capabilities to ensure the timely detection of PCOS/PCOD diseases.**

Keywords: ***PCOS, PCOD, Deep Learning, Convolutional Neural Networks, Risk Stratification, Women's Health, Early Detection, Predictive Analytics, Medical Diagnostics, Deep and Machine Learning Ovarian Follicle Detection, Clinical Risk Prediction, Risk Stratification, Predictive Analytics, Early Detection, Women's Health, Reproductive Health, Hormonal Imbalance Analysis, LH/FSH Ratio, Anti-Müllerian Hormone, Body Mass Index, Metabolic Disorder Assessment, Supervised Learning, Binary Classification, Feature Engineering, Feature Selection, Feature Importance Analysis, Ensemble Learning, Random Forest, Gradient Boosting, Support Vector Machine, Logistic Regression, Multimodal Data Fusion, Ovarian Follicle Detection, Clinical Risk Prediction, Risk Stratification, Predictive Analytics, Early Detection, Women's Health, Reproductive Health, Hormonal Imbalance Analysis, LH/FSH Ratio, Anti-Müllerian Hormone, Body Mass Index***

I. INTRODUCTION

Believe it or not, PCOD/PCOS can be the most stubborn hormone culprits affecting women well into their reproductive years, tampering with the functioning of the ovaries—disturbing the balance, regulating the regularity or irregularity of the cycle, increasing the level of androgens, and providing a breeding ground in the ovarian tissue for a whole bunch of budding follicles. Because every PCOD/PCOS case is different, they slip through the cracks—unrecognized or diagnosed often too late— increasing the risky potential for future problems like infertility, weights gained, resistance, type 2 diabetes, and heart problems.

Also, classic diagnosis relies on what the patient tells the clinician, blood hormone level testing, and ultrasound scanning, where a clinician reads results. The whole thing can take a while, is subjective, and relies on the practitioner's interpretation. Small, critical factors can be missed on an ultrasound scan, leading to misdiagnoses, so there is a real need for a smart technology that provides precise results.

Machine learning techniques, especially deep learning, are advancing in such a way that the result could be breakthroughs in the analysis of images in the medical field, as well as in the prediction of a patient's illness, where deep learning, especially convolutional neural networks, excels at feature detection in images such as ultrasounds, which show patterns in the distribution of follicles, ovarian structure, etc., that indicate PCOD/PCOS, while at the same time machine learning techniques are effective at weighing clinical probabilities such as age, BMI, levels of hormones, etc.

The project aims to present a complete intelligent system in which PCs can utilize ML and DL to anticipate and identify PCOD-related issues in women. Among other things, this project is implemented in a format of a web application using a Python library named "Django"; this application combines CNN technique and ML predictions to provide a full solution for diagnostics. Use of this application can facilitate seamless interactions between image processing and ML predictions using a Python library named "Django."

II. LITERATURE SURVEY

Polycystic ovarian syndrome, also referred to as PCOS, is a hormonal problem that ranks as a common hormonal problem women have to face around the globe. This condition can also help women to avert other serious diseases later on, as PCOS would act as its early detection. In the year 2024, research on employing a novel approach in computer science called 'machine learning' involving a combination of support vector machines, coupled with a feature selection approach, was conducted by researchers Tanvir Mahmud, S. A. Sabbirul, Mohosin Naim, on a PCOS approach.

Another major breakthrough in a more sophisticated system of diagnosing PCOS comes from Nethra Sai et al., who incorporated a more refined and sophisticated model of diagnosing PCOS in 2024 using a combination of "ultrasound imaging and patient clinical data using ML and DL algorithms." Further, "ResNet-50 model has been utilized to extract image features by using a correlation technique to select features from clinical patient data." Further classification has been accomplished using methods such as "SVM," "Random Forest," "Logistic Regression," etc. Such a model of diagnosing multi-modal PCOS combines both image and clinical patient data to give more accurate results compared to a singular model of diagnosing PCOS using a single type of data.

In a study conducted in 2024, Natasha Leslie, Angga Aditya Permana, and Analekta Tiara Perdana tried to evaluate the accuracy of the algorithm for PCOS classification based on the symptoms and characteristics experienced among the patient population. The authors were able to obtain varying levels of accuracy with different combinations; the maximum accuracy was 100%. The scenario posed for the effective implementation of machine learning algorithms in PCOS diagnosis seems favorable; despite that, certain limitations were also pointed out.

On alleviating the hassles associated with testing in PCOS, another study looked at the tedious nature of testing, as well as its cost implications, and introduced an early warning system that would utilize clinical as well as metabolic markers of PCOS to ease the process, cost, as well as the associated time spent in testing, as proposed in a study done by Shivani H. C., Vidyashree, as well as Yashaswi R. in 2023.

The study authors conducted experiments with the Random Forest classifier algorithm and other machine learning-based tools such as CNN on the developed dataset to detect PCOS cases among women. The intention of the study was to create an environment with a smooth workflow to detect PCOS across the female population, with factors of population density taken into consideration.

More recently, in 2025, a research paper by R. Parvathi and Prof. Dr. P. Geetha analyzed the topic of "Prediction of Polycystic Ovarian Disease by Applying Deep Learning Concepts to Medical Data from Kaggle Datasets." The researchers pre-processed the information by handling missing values and unnecessary information. The researchers have tested the deep learning models DNN, RNN, and CNN and have used precision, recall, and F-measure to interpret the results, and the researchers concluded that the results are favorable and can cope with the complexity of the information with improved accuracy.

III. METHODOLOGY

The system of interest utilizes the artificial intelligence of machine learning as well as deep learning to create predictions as well as detect Polycystic Ovarian Disease (PCOD). It begins by recognizing the information streams, which include the ultrasound images as well as other related clinical parameters of age, BMI, menstrual disorders, hormones, thus laying the backbone to create intelligence to identify the PCOD patterns appropriately.

Before running any model on the data, there is thorough preprocessing of the data. For example, when dealing with ultrasonography images, they need normalization of resolution. This is done so that there is a smooth distribution of pixels. Then there is an additional process known as contrast enhancement. This process reduces noise and maximizes image visibility. There is data augmentation. For example, rotations and flips of images can be done to prevent data from becoming stagnant. Clinical data has some preprocessing done on it.

Various techniques are integrated into the model to improve the level of accuracy attained. The convolution neural network is developed with the purpose of classifying the images received through ultrasound as either PCOD Positive or PCOD Negative. A Random Forest or a Support Vector Machine technique is employed to assess the risk of a patient having PCOD. The approach employed by the models is that of supervised learning. The images are divided into training, validation, and test sets.

While the performance of the model is monitored with all the regular parameters like accuracy, precision, recall, F1-score, and the confusion matrix, the tuning of the model with the appropriate parameters minimizes the error while the model makes predictions. Finally, the saved model can be deployed on the Django framework.

System Architecture

The system architecture of the PCOS and PCOD detection system is presented as modular, where the components of the system—i.e., gathering of information, image preparation, deep learning model preparation, web layer—can be observed as modular components of the system. The program begins by accessing the ovarian ultrasound images from the Kaggle site, where the relevant images can be obtained as the input to the system.

The process of obtaining the dataset requires obtaining the ovarian ultrasound images from reliable and publicly available sources like Kaggle. This dataset also contains labeled images of ovary conditions that are normal as well as those suffering from PCOS or PCOD. This type of standard dataset will also help in obtaining original and reliable data during effective training of the model. The images obtained are purely essential to implement different deep learning algorithms as part of the whole system. It also requires some

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preprocessing techniques to obtain high-quality images and maintain uniformity across all of them. The images are resized to a particular dimension to meet the constraints of Convolution Neural Networks (CNN). Normalization of pixel value and different techniques of reducing image noise to emphasize important features of ovaries like size and arrangement of follicles are also part of preprocessing. While pre-processing, data which is irrelevant, damaged, or unlabeled is deleted manually. There are also some data augmentation techniques, which may include rotations, flips, as well as zooming, helping the models learn better. This stage of pre-processing is important so as to enhance the accuracy, robustness, as well as reliability, of the models designed for the diagnosis of PCOD and PCOS.

2. Model Development: CNN + Machine Learning

Basically, the development phase of the model involves creating intelligent systems that can make predictions and detections concerning PCOD/PCOS on the basis of clinical data analysis with ultrasound images coming from the ovaries. For this objective, the project uses the classic approach that has been mixed with deep learning in such a way that the model uses the best features of both.

For machine learning predictions, input features include clinical/demographic factors like age, BMI, regularity of menstrual cycle, hormone levels, and other lifestyle factors. After preprocessing, these input features are used to feed supervised learning models, including logistic regression, support vector machines, and random forests, that look through these data patterns to compute a certain probability for PCOD. In order to increase the accuracy, feature importance is performed.

To achieve the detection of ovarian ultrasound images through deep learning approaches, Convolutional Neural Networks are utilized as the tool for image interpretation. Different types of CNN architectures are considered for the proposed approach. They are custom CNN architectures, LeNet CNN architecture, and SqueezeNet CNN architecture. Through the CNN architectures considered in the proposed work, different features related to the distribution of follicles in the ovarian ultrasound images are picked up.

The metrics for evaluation of the model followed by the experimentation phase are the same, which includes accuracy, precision, recall, the f1 score, as well as loss. This makes it possible to assess which model yields the better results in terms of efficiency. The model results from the experimentation phase, which performed the better, are combined with the Django web app, which helps in real-time prediction as well as the detection of PCOD as well as PCOS.

Formerly, the

The backend of the entire system is developed using the Django framework, along with the Python programming language. It acts as the connecting hub between the user interface, as well as the various deep learning models. Among the tasks performed by the backend include the loading of the .h5 files containing the loaded models, as well as the processing of user actions, including video upload. Additionally, the backends handle the real-time extraction of video frames as well as audio from the videos, after which they go through the various CNN as well as Random Forest models. This eventually leads to the generation of results detected, which is later filtered in the form of clear output so the results can be visualized through the frontend.

Frontend Development:

Furthermore, the interface in interaction with the user will be created such that the HTML will be used as the programming script with the help of CSS and JavaScript programming languages to provide an interactive interface for the users of the app. Various pages will be created in the app interface. This will include the main page of the app as the landing page; another page will be created for the users of the app to enable the input of video data.

Database Integration:

The database system employed by the application is SQLite3. The database maintains vital information such as users that have registered to use the application, users that have logged in, records of video uploads, and results of detections carried out by the application. Deployment Using Django Framework: Once the development phase is done, all parts integrate with Django to create a complete web application. Django creates an outstanding union between the frontend and backend by allowing real-time computation and interaction between them. Once this application is deployed, it will be fully functional and able to perform deep fake face recognition and deep fake audio recognition with high efficiency. Final The system provides the user with the classification in an interpretable manner through the web interface in the form of the classification results. The system provides the classification in the form of "PCOD DETECTED," "PCOS DETECTED," or "NORMAL" along
with the predicted value of the degree of intensity through a "confidence score." A user can make a quick accurate diagnosis of the disease through the deep learning models in the form of "CNN" and "ML" techniques.

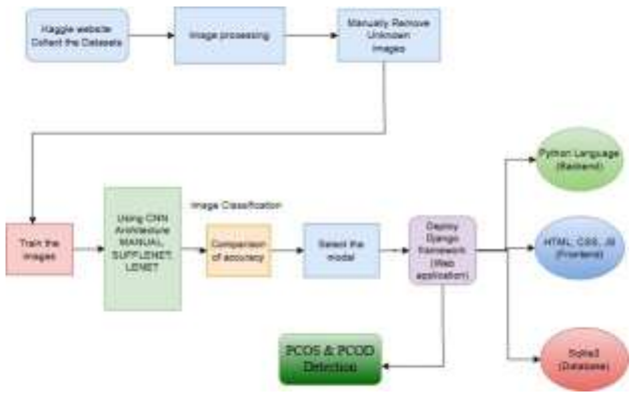

Fig: Architecture Diagram

Data Analysis:

"The core of any computer system attempting to predict something is to dig into the data to identify patterns, relationships, and key factors." For this project, the focus is on the patterns within the data set of the image of the ovaries using ultrasounds and a complex set of information such as age, BMI, irregular cycles, hormone levels, etc.

The exploratory data analysis will help identify trends and relationships that may exist as well as identify possible data outlying issues. It will start with calculating some statistical values such as mean, median, and standard deviation to have an idea about the data set. Additionally, data visualization plots such as histogram and correlation matrices will be utilized to observe relationships between various variables

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that may affect PCOD prediction risks.

In the imaging side of the picture, the process begins from the pre-processing feature extraction region, followed by the application of Convolution Neural Networks (CNNs). The CNNs detect the patterns employed in ultrasound images, including the size of the follicle count, which is of primary interest when diagnosing PCOD.

Using the structural clinical information and the images, the system can effectively fuse the two types of information and consequently improve the levels of prediction accuracy. The evaluation metrics are expected to consist of accuracy, precision, recall, F1 score, and a confusion matrix. Broadly speaking, the analysis of the information can support an intelligent system geared towards the early screening and appropriate care at women's health services.

MODULE DIAGRAM

GIVEN INPUT EXPECTED OUTPUT

Input: data

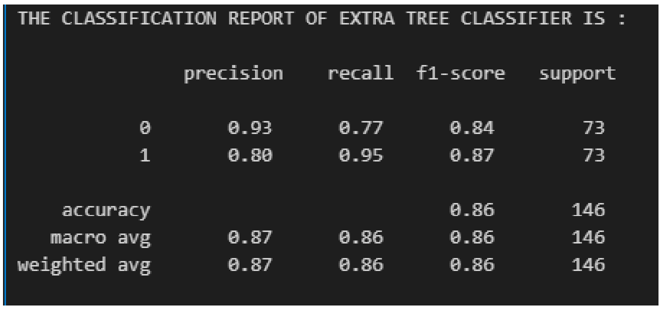
Output: visualized data

Algorithm implementation:

When it comes to machine learning in particular, it's vital to continually test how well these various machine-learning algorithms continue to perform relative to each other. Create test harnesses in Python with the scikit library for comparing multiple machine-learning algorithms. This test harness should be treated as a template for building other test harnesses for your particular problem of literacy.

Different machine-learning models have unique performance characteristics that need to be evaluated as well.Using cross-validation, you can get a rough approximation of the potential performance of each of your models when given new, unknown information. That will point you towards one or two from your line of models that are performing best.If a new set of data is available, there are various ways to examine the data so that a better perspective is obtained. Similarly, when there is a question of model selection, it is better to examine the performance from various perspectives to narrow down the choice to one or two models. It is also possible to visualize the various aspects of performance obtained from the models so that robustness is measured to

Obtain the best models.

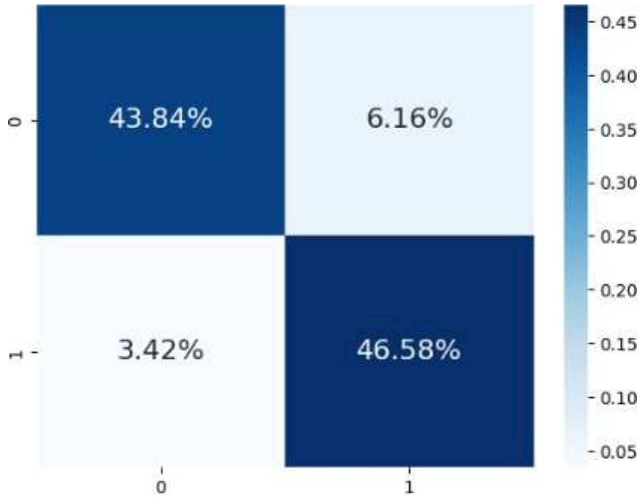


```
THE CLASSIFICATION REPORT OF EXTRA TREE CLASSIFIER IS :

              precision    recall  f1-score   support

           0       0.93      0.77      0.84        73
           1       0.80      0.95      0.87        73

    accuracy                           0.86       146
   macro avg       0.87      0.86      0.86       146
weighted avg       0.87      0.86      0.86       146
```



LeNet takes its place as an early instance of CNNs created back in the early 1990s by LeCun et al. It represents an impetus to deep learning with an initial application to readings of handwritten digits as found in checks and addresses. It introduced convolutional networks for image recognition and computer vision tasks.

The architecture is based on a number of key layers:

- Input: In this layer, the image to be classified is fed into the network. The LeNet network expects the image to be grayscale and of size 32x32 pixels representing a handwritten digit.

- Convolutional Layers: To achieve the simple extraction of features from the images, the model has employed two sets of convolutions. Each set of these convolutions employed several filters on the entire picture, scanning through the picture as if the filter were moving to create the feature maps.

- Pooling (sub-sampling): Following every convolution operation, a reduction in size of the image occurs in both directions while maintaining essential information in these reduced forms to reduce computation.

- Fully Connected Layers: The feature maps from the previous step get fed into one or more fully connected layers that finally make the decision on the basis of the features.

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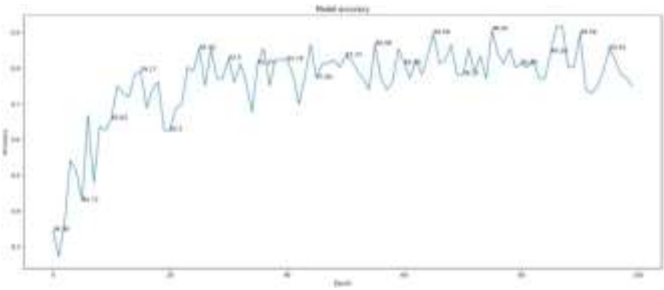
- Output: The last fully connected layer represents the prediction made by the network, normally having 10 outputs representing the numbers 0-9, respectively. Long before the rise of deep learning, the architecture of LeNet had fewer layers than those presently familiar, e.g., ResNet, VGGNet, Inception, etc. The concepts introduced in LeNet, however, are essential to understanding the development of advanced architectures for image recognition, including state-of-the-art CNNs — a boost to neural networks in the early 2000s.



Deployment:

Django (Web Framework):

Flask is considered a microframework because it only provides a lightweight core without bundled tools or vast libraries, such as database abstraction or form validation, but almost anything can be done with third-party packages. Nevertheless, Flask has an extension that supports object- relational mapping, form validation, file uploads, authentication mechanisms, and most other web framework- related features. Due to the minimal and flexible philosophy, in Flask, the complete control of the project structure remains with the developer, who can choose only those components that are required. This simplicity makes Flask quite easy to learn and to set up in no time. It is preferred for beginners, rapid prototyping, small applications, APIs, and also in microservices architecture.

IV. RESULT AND DISCUSSION

The performance of a PCOS detection system was assessed by executing it using a cleaned dataset and comparing it to ML and deep learning algorithms' performance. Out of all ML algorithms that are not deep learning algorithms, it was observed that both Random Forest and Gradient Boosting had similar performances with an accuracy of around 90%. They outperformed other ML algorithms like SVM and Logistic Regression that had an accuracy of around 85-88%. This illustrates that ensemble algorithms have an edge in addressing non-linearity of clinical features.

For the deep learning path, the Artificial Neural Network achieved 92% accuracy and hence was able to read the complex interrelation between the different levels of hormones, BMI, and ultrasound. It was able to come up with probability levels in relation to PCOS diagnosis for different patients. In trying to avoid overfitting, the model had various strategies such as the use of dropout and regularization to ensure good performance in unseen data.

The analysis identified LH/FSH ratio, AMH levels, menstrual abnormalities, and BMI as most impactful in determining PCOS.

Random Forest analysis

To confirm these clinical findings, Random Forest analysis has been performed on the dataset.

The feature distribution visualization from Random Forest analysis clearly indicates differences between PCOS and Non-PCOS classes on these identified features.

From the overall findings of the study, it can be stated that the potential of the proposed concept of the hybrid form of machine and deep learning approaches can be considered for the early identification of the subject of PCOS. While the proposed approaches can aid the clinical staff in making the required judgments regarding the subject of PCOS, the study highlights the appropriation of the AI concept in the field of increasing the level of precision in the diagnosis of the subject of PCOS.

Among the conventional ML techniques used, RF and GB obtained the best performance, i.e., with an accuracy of approximately 90% and 89%, while the conventional Logistic Regression model and SVM were slightly behind, ranging from 85 to 88%. Moreover, the ensemble model performs the best because it effectively deals with the concept of feature interactions as well as variance reduction. Also, RF was used to determine the important features, which are predominantly the case when there are hormonal imbalances, such as the LH/FSH ratio and AMH

V. CONCLUSION

A pre-processing dataset was utilized in validating PCOS system detection, where comparison of machine learning with deep learning models took place. In the list of ML techniques utilized, Random Forest and Gradient Boosting were on top, with each class of algorithms nearing 90% accuracy. SVM and Logistic Regression came next and scored slightly lower, between 85-88% accuracy.

For the deep learning side, a fully connected artificial neural network was used and resulted in the best accuracy of 92%. The improvement in the accuracy indicates the potential of the ANN to better recognize the relationship between the patient's levels of hormone, BMI, and the results from the ultrasound. The ANN was also successful in providing the predicted probability value for the patient's having PCOS.

For the ANN to prevent overfitting, several attempts were made on the hidden layer using the regularization method and dropout.

To achieve this, feature importance was studied, and the result of the feature analysis was used to validate the key findings based on the LH/FSH ratio, the importance of the level of AMH hormones, menstrual disorders in the cycle, and the importance of BMI in the features in differentiating the individuals from PCOS from those not suffering from the disease. This was in close agreement with the importance derived from the RF classifier. From the visual result of the comparison of the features of individuals with and without PCOS, the difference was clear. The study demonstrates the potential benefit that is derived from the integration of Artificial Intelligence, as well as Machine and Deep Learning to improve the early and accurate identification of PCOS. Additionally, aside from making identification or classification in binary form, the program is also able to offer risk scores, allowing the decisions to be made while enabling the patients to fully understand the concept behind their health condition.

From the models discussed above, the machine learning models provided rapid solutions with easily interpretable models, whereas the deep learning models managed to advance the accuracy and generalization of the models slightly. Meanwhile, the ensemble models such as the random forest models found an excellent balance between performance and interpretability of the features involved in the models. At the same time, the deep learning models did an exceptional job in the recognition of complex patterns in the data.

There are some limitations in this context; the data set used was moderately sized, so this limits the degree to which new population groups can be predicted based on this system. There are some aspects, like using ultrasounds, that can be accurate depending on the person used to examine the patient. There could be an expansion in the size of the data set, including different types of genetic and metabolic information, creating real-time predictive tools so that the system can be used continually to monitor patients effectively. Explainable AI can also be a great addition in this context.

On the whole, the integration of the two models appears promising in terms of the early diagnosis of PCOS, as well as the reduction of the timeframe involved in the diagnostic process. By giving the user a combination of the results of both classification models, as well as the predictive results, it helps the person make informed decisions, which can prove highly useful.

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