A Robust Approach Towards Detection of Polycystic Ovarian Syndrome (PCOS) using Artificial Intelligence

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Abstract— **The menstrual health of pregnant women around the world is deteriorating over time which is the prime cause for the increase in abortion rates, miscarriages and instances of infertility. Polycystic Ovarian Syndrome which is an endocrine disorder with hormonal changes in women and characterized by the Follicular Cysts that get formed in the ovary and there is an increase in the level of male hormone in the female body thus causing Hirsutism and skipped periods. The early detection of PCOS during early adolescence is not well-understood and the symptoms can be properly discovered in the later stages of life, and could prove to be even more detrimental. The purpose of this research is the early detection of PCOS using methods and instruments of Artificial Intelligence with a reliable accuracy which can help the doctor in speedy diagnosis of a patient and reduce the time-to-treatment of the patient. The parameters that are used as inputs to the model are physical attributes that can be measured and evaluated using minimal equipment which can be obtained with ease. The most significant segment of any Machine Learning research is the collection of data and the preparation of a clean data set which can be used for the prediction or classification of any particular subject of interest. In this system, a data set is obtained from a patient survey of 541 women during medical examinations and clinical surgeries, and also laboratory experiments. The system consists of two basic functional parts, the pre-processing of the data and classification of the categories based on the features selected. The binary classification of PCOS is processed by using a fine-tuned Random Forest Classifier, which turned out to be of the best fit, having an accuracy of 92 percent and having a AUC score of 0.97.**

I. INTRODUCTION

In the current world paradigm, Polycystic Ovarian Syndrome (PCOS) is regarded as one of the most common disorder of the endocrine. The extent of which is certainly detrimental and invariably not favourable to the target population it affects, which is all women irrespective of race/ethnicity of reproductive age. According to studies, it is noted that the most delineated cases of PCOS are seen in women aged from 18 to 45 years. The most alarming trivia that we encountered during the course of our research is the fact that most cases of PCOS, goes unnoticed and hence are not properly diagnosed. Like any other disease, PCOS also has certain physically prominent symptoms, few of which includes, obesity, excess growth of facial hair, menstrual cycle irregularities among many others but what is more problematic are the after effects of the disease which leads to increased chances of miscarriages, abdominal disorders, obesity, type-2 diabetes and a perpetual state of affliction in patients. PCOS can be nursed to an extent through controlled medication and through regular monitoring of the affected area with the aid of scanning procedures like with the use of the ultrasound method. However, increase in male hormones in the patient being one of the direct effects of PCOS, the patient in question becomes more prone to infertility and vulnerable to cardiovascular diseases, which is absolutely not desirable. In fact, PCOS is the one of the leading causes for infertility in women. These factors denote the underlying reason and importance for the early detection of PCOS, and thereby highlighting our motivation for this research.

With the advent of Artificial Intelligence in the past two decades, used as a tool common to even diametrically opposite domains of research, we now find it to be extremely prevalent in every sphere of research especially which constitutes of detection, prediction etc., the sole reason for which is the sheer ease and precision with which one can compute through various methods which are at our disposal. Amidst these technological breakthroughs, the integration of Artificial Intelligence used in detection algorithms in healthcare research deserves special attention, essentially because, it does not only reduce the chances of a particular ailment get unnoticed but also helps to increase the overall efficiency of the diagnosing structure, which is currently prevalent in the world. It is needles to say that the application of statistical methods on data and thereby training the same and predicting results is meaningless without the medical expertise of a doctor, and therefore in this paper, we present a novel approach wherein we take all the relevant features of diagnosing PCOS into account and thus predicting the possibility of a patient having the ailment or not. Through this paper, we aim to provide the medical researchers and practitioners of this domain with a helping hand so that one can collate all the physiological and metabolic parameters and then diagnose the patient in question primarily with the dexterity of their medical expertise, alongside our algorithm for better assurance and lesser chance of missing out on relevant insights which often goes unnoticed to the naked eye.

I.I Need for detection Algorithm

Artificial Intelligence is a sub-field of Computer Science, which is playing a vital role in the enhancement of human potential in recent decades. The deployment of AI in many different areas is showing its tremendous impact by proving itself to be highly accurate and precise with exact and valid results. Machine Learning is now a sub-field of AI which deals with data and its processing. In this paper, we use medical data collated from various hospitals which were analyzed and visualized to dig out and jot down the most unique and deterministic characteristics of a disease.

I.I.I ***Potential of AI in Biomedical field:***

We have implemented AI with its integration in the medical diagnosis field for new modern analytical platform to combine its clarified practical and computational approaches with the intuition of professional doctors in order to provide better-diagnosing structures. These structures when implemented with great vigilance, might be very accurate which might even eliminate human errors. With the evolution of the elaborate medical information assembly and an increase in health-related problems, a proper diagnostic tool might be an important tool for the confidence in doctors as well as that of the patients. As with the increment of parameters and information governing a disease and lack of adequate time for diagnosis of each patient might lead up to misdiagnosis of a disease.

Artificial intelligence provides a computer with a brain, which in return gives the computer the power to perceive, process, classify and detect something with the help of information provided to the database for the sake of logic and probability. This permits the computer to do various operations on multiple examples with the help of processing power, thus making the computers work for detection of that disease and with the help of physicians, the most relevant features governing that disease are filtered and taken into account for the identification of the same. The deployment of these kinds of models helps the doctor to keep an account of all the knowledge in laboratory diagnosis reports, helping in decreasing the time for diagnosis of a disease. Physician's proper domain knowledge alongside with the AI model increases the accuracy and precision of the predicted results.

AI is a supplementary technology, which gets put through to amplify the performance of doctors, nurses, and medical equipment operators to effectively carry out their tasks. AI won't pose any threat to the the the doctor's profession as a replacement but rather it can act as a valuable assistance in simplifying the ever-complex medical challenges.

I.I.II ***Extensive databases for ML:***

By the virtue of electronic health care records (EHRs), all varieties of data get stored in the hospital's respective databases which makes huge amounts of exploitable data available to us, if proper access to the same is allowed. That holds affirmative for all kinds of data–pictorial, electronic signal reports and labeled data that is manually collected with the help of medical equipments. Using these different types of data, signal processing is used to get their corresponding integer values or other computer-understandable formats. Machine learning models trained on the targets to give predictions on new unseen test data to the model. We also observed that the more structured and digitized the data in hand, the more significantly the patterns are visible and therefore we obtained valuable insights from the same, which significantly helped with our research with regards to detection of PCOS.

With the advancement of tools like IBM's Watson, the healthcare industry is being aided in medical management platforms to grow and develop extensive amount of data and its evaluation. IBM Watson can store a lot of information that can be used to infer upon and hence get insightful results. Similarly, Google DeepMind health operates in congruence with physicians and researchers to create technologies that incorporate machine learning with their medical expertise to detect the main root causes leading up to a disease. Such data collected helps the machine to learn, classify and identify patterns more efficiently by allowing the model to train on any other instances. The data we used here is supervised meaning that it is labeled with a target value. This target value is the disease that is being governed on the features that the model is fitted with. Then segregation was done by prioritizing the most important features from the bundle that was assembled.

I.I.III ***Rapid Recognition of diseases*** Deployment of AI in many medical sectors is assisting in the detection of diseases like cancer, diabetes, abnormalities in the heart, and several other diseases at their initial stages very accurately. As claimed by, American Cancer society that 1 in every 2 mammograms are found to be erroneous which can be overcome by AI's fast technology through quick diagnosis assessment giving 99 percent accuracy 30 folds faster.

That is why in our model Polycystic Ovarian Syndrome (PCOS) is set as the target to do binary classification on it with the help of Machine Learning algorithms. Here we considered different external and physical features of a human being that influences PCOS, classified according to the data and our target, and made predictions depending on it.

Most significantly, machine learning is performing the heavy lifting of difficult statistical problems which indicates the correlation of a feature with a disease. This leads to quick and efficient detection of diseases which might lend the doctors more time to take further steps in diminishing the factors whose imbalance in the first place might be causing the disease. This fulfils the need for rapid and meticulous detection of diseases in the ever-growing population of the world.

I.II **Challenges faced in detection of Polycystic ovary syndrome**

It is crucial to identify the challenges that are being encountered in efficiently diagnosing PCOS; not only it has to be ruled out from other related ailments, but also because there is a high chance of the patient becoming increasingly vulnerable to grievous conditions like obesity, breast cancer, diabetes, heart diseases, cardiovascular diseases and ovarian cancer. Needless to say, it is vital to detect PCOS as meticulously as possible.

I.II.I *Adolescent v. Adult Diagnosis*

One major point of discussion that we observed to be the subject of concern in many studies was the varying criteria for diagnosis in case of this disease. The diagnosis can turn out to be particularly arduous in adolescents, in menopausal or those who are on the verge of it. In the case of adolescents, various signs of PCOS may be conventional while going through puberty, such as acne or irregular cycles. This makes the demarcation between signs associated with PCOS and regular activities as seen in a healthy woman difficult to establish. Also, from the observation that the traces of PCOS are many a time observed in ovaries while they are developing during puberty, it is not wise to make use of medical imaging techniques in detection of PCOS in the adolescent group [1].

On whether the adult criteria of diagnosis should be implemented on adolescents is still a matter of dispute as seen in numerous studies and researches [2]. Although there are three major ways in which polycystic ovary syndrome can be identified in adults - checking for high androgen levels, irregular menstrual cycles, and cysts in the ovaries [3], no such defined or unanimously accepted ways exist employing which the same can be identified in adolescents.

I.II.II. *Confusion with other similar diseases*

PCOS is deemed to be a ‘diagnosis of exclusion’, meaning it is necessary to exclude other common conditions with symptoms akin to PCOS.

Regarding certain other symptoms/signs associated with PCOS, it is difficult to establish whether the particular sign/symptom is a cause or has occurred as a result of the disease. Say obesity, which is a common associated feature; there is very little clarity in whether the disease makes women susceptible to obesity or whether obesity itself provokes the said syndrome. PCOS poses differently in each woman during their reproductive age. Its symptoms alter with age, weight and race, hindering perfect diagnosis. Many patients do not show all the classical symptoms (for instance, it has been found that many women do not have cysts in their ovaries, much in contrast to the innuendo of the term ‘Polycystic’), which is why in the course of the research we found that more than 50 percent of the women are not diagnosed properly.

I.II.III *Complexities revolving around ultrasound testing for PCOS*

After digging through numerous scholarly articles, we were able to conclude that the detection of the syndrome through ultrasound is not accepted extensively, which is the most relevant diagnostic imaging technique used in gynaecology. Unfortunately, it has primarily been observed that tiny follicles (size varying between 2 to 6 mm) in the form of cysts are not traceable by ultrasound. Again, real-time testing of PCOS can prove to be a gruelling exercise as follicles apart from those in the above-mentioned range are often cocooned in networks of blood vessels and tissues, making it problematic to detect them, thus escalating the error rate [4].

I.II.IV *AI for healthcare: Problems with data accession, collection and analysis*

Having introduced some of the medical challenges above, the recurring problems arising with the introduction of AI in healthcare are also needed to be addressed.

A new frontier has been presented with regards to the deployment of AI tools and techniques in potent clinical environments and methodologies. Irrespective of our disease under focus, a very common complication that can delay progress is the quality of data. Data is often acquired from online dataset repositories if not collected over a period of months by researchers themselves. In the case of the former, the authenticity, as well as the legitimacy of the data, can sometimes be questionable if not backed up by experts or any relevant documentation. Erroneous data, misprint, mismatched entries, insufficient data or null points can make AI algorithms vulnerable to error and unreliability, which is absolutely not desirable when a biomedical analysis is under consideration. Very clean, precise, complete and multifaceted data is required to train AI algorithms so that they can provide highly optimal as well as satisfactory results.

Other possible threats that we found out during the course of our study include algorithmic bias, manipulation and logistical issues in the implementation of algorithms [5]. Said logistical issues revolve around limited access to healthcare data (pathological, EHRs, healthcare insurance information, electronic imagery data etc.), which are archived in huge databases and medical systems.

I.II.V. *The question of ethics, security and patient satisfaction*

The onset of Artificial Intelligence in the field of healthcare has instigated numerous debates regarding the assortment of threats that it poses concerning information security, dependency and ethics concerns, not just the technical issues that we have discussed till now. Even though AI has already made huge strides in this field and has, in some instances, proven better than actual doctors and medical practitioners, it has been deduced through extensive research that many patients would rather not subject their medical details to the tools of AI, citing issues with trust, transparency, accuracy and questioning the maturity of the algorithms. According to a recent consumer survey conducted by Accenture [6], only about 50percent of the mass was willing to let AI diagnose them whereas about 49 percent showed interest in letting an AI coach help them with chronic ailments. In the 2017 HIMSS Analytics poll, more than two-thirds of the poll takers were reluctant to resort to AI due to its immaturity.

It has also been discussed by researchers that using artificially intelligent diagnostic and treatment methods can prove to threaten the way patients deal with providers, point-of-care technology tools and ultimately data. Especially in a developing nation like India, reliability over AI technology in the biomedical field has still a long way to go even though it is supposed to be devoid of social biases and assumptions. Also, the fact that this technology is still a foreign concept to many medical consortia, making every (or as much as possible) procedure in this field 'AI-centric' might take some more time.

Another very interesting concern that has been widely addressed is of data security. In a Health IT Analytics survey conducted by SAS [7], only about 35 percent of patients very assured that health data meant to be personal was being stored securely. With the advent of AI, a new challenge surrounding data privacy has risen since most healthcare datasets are massive and there is a need for a new and non-traditional approach to data sharing, usage and reuse.

I.II.VI. *Complications in comparing different algorithms*

Without correlation on the same independent test set that is associated with the population under consideration while utilizing the same performance metrics, it is difficult to predict which algorithm is more inclined towards optimal performance best suited for the patients compared to the rest of the algorithms.

I.II.VII. *Susceptibility of the algorithms to error*

Much like any other physician, AI algorithms have sometimes given results that are faulty and completely inaccurate. Primary causes governing such miscalculations are insufficiency and inaccuracy of data, manipulation, misinterpretation of algorithm results, lack of explicit explanatory knowledge structures (particularly in deep learning models) and most importantly, the introduction of noise elements, leading to misdiagnosis.

I.III **APPLICATIONS**

AI has found its applications in several biomedical fields such as cancer treatment, radiology, endocrinology, neuroscience, gynaecology, including our focus syndrome: PCOS. Polycystic ovary syndrome is a rather complicated disease, difficult to centralise in a common domain of diagnosis and treatment, mainly because of the symptoms varying with age groups and race as well as misdiagnosis due to the diseases' similarity with other ailments . The recent advancement of AI into this field has proven to provide an intuitive understanding and also the subsequent application of suitable algorithms and methods into possible treatment and further research.

To assess the situation on the ground level, it has already been established that the detection of this syndrome in adolescents is different from that in adults. In such a scenario, AI can play a significant role in easier detection across various parameters with minimal chances of error. PCOS is a rather chronic ailment and may require a person to make frequent visits to the doctor over a long period of time. In this situation as well, AI can help save time and effort by not making it necessary to consult a doctor everytime with overwhelming amount of data under consideration.

Specially in a country like India where the average doctor to patient ratio is 1:1,000 (as of Nov. 19, 2019) [8] and the nurse patient ratio is 1:483 (as of Apr. 14, 2019) [9], the alarming deficit of first-hand medical care can be substituted by AI. It also eliminates the the need for costly tests and appointment charges.

Advancement of follicular segmentation methods as well as classification of ultrasound images has also helped in the study and diagnosis of PCOS efficiently with many algorithms such as SVM, CNN, Bayesian classifier etc. returning with high accuracy, thus ensuring reliability.

PCOS is also one those cases where medical data is needed to be recorded over the entire course of treatment and diagnosis. Such data management and storage becomes convenient and hassle-free with the aid of AI and digital automation. This also facilitates quick tracing and analysis, way faster than sometimes even the traditional medical means themselves. With the help of an application or other such interface for direct evaluation against a database of previous records and assistance with regards to further course of action, the process can be sped up and simplified to a huge extent. AI can further be applied to conduct research studies on this syndrome to better understand the complex nature behind it so that a definite treatment can be determined along with biopharmaceutical development.

In conclusion, until human supervision is not absolutely necessary specially in the situation of complicated cases, AI can be utilised as a good substitute in order to diagnose, treat, and medicate PCOS.

II. LITERATURE SURVEY

Techniques for quantitative three dimensional rendition of two dimensional tissues or other planar segments of organs called stereology was proposed by Adiwijaya et al. [10] in his paper and was used to measure the diameter of the follicles in ovaries by means of Euclidean distance measurement with 78 percent accuracy. Dewi et al. [11] made use of the Gabor Wavelet for image feature extraction in order to classify the ultrasound image classification into SVM (82.55 percent accuracy), KNN (78.81 percent accuracy) and NN-LVQ. Particle Swarm Optimization, the evolutionary computational method that made its breakthrough in the paper by Kennedy et al. [12] in 1995 was used in another paper by E. Seatiawati et al.[13] to cluster ultrasound images into 'swarms'.This grouping simplifies optimization and other machine learning methods become easy to implement. Zhong Qu et al. [14] introduced the one dimensional Otsu technique that has proven to be quite reliable in gray-scale image processing and straight-forward computational method. Limitations of Otsu were also discussed in the same paper and the idea of Entropy with hinged technique was mediated to overcome the said limitation. Huang and Wang [15] introduced the fast algorithm called Two Stage Multi-Threshold Otsu method (TSMO) that minimises the iterations in calculating between class variance in image data, which can play a vital role in PCOS for most of the data available nowadays is image based. Liu et al. [16] put forward in their paper a derivative of the Otsu technique in to two-dimensional format and the threshold value is changed into a vector, thus significantly to enhance the segmentation outcomes. Yinhui Deng et al. [17] discussed in their paper about an autonomous system made for PCOS diagnosis in order to eliminate speckle noise as well as improvement of the watershed algorithm. Narayan et al. [18] proposed a fully automated system for detection and segmentation through three dimensional ultrasound imagery.An interesting approach was described in a paper by Liu et al. [19] called the Pigeon Inspired Optimization (mono-objective continuous optimization algorithm) which can prove to be helpful in obtaining the desirable threshold value for follicle segmentation purposes. This paper also showed that the said technique performed better than the Invasive Weed Optimization method. Identification of PCOS on the basis of Gabor based features and the Elman Neural Network was proposed by Thufailah et al. [20], where the Elman Neural Network has been insinuated to come out with much more effective results than the existing machine learning processes. An intricate rule for follicle identification was designed in [21] by first carrying out the denoising of ultrasound images with the Homogenous Region Growing Mean Filter(HRGMF) , followed by edge detection using Kirsch's operator and then evaluation based on three parameters (area, eccentricity and compactness). Hiremath and Tegnoor [22] made use of the contourlet transforms and Gaussian low pass filter for denoising ultrasound data. Contourlet transform achieved 75.2 percent follicle tracing accuracy whereas Gaussian low pass filter returned with 62.3 percent accuracy. In the paper by Ashika R. [23], removal of speckle noise in ultrasound images was achieved by means of Fuzzy C-means clustering. Soft threshold method was used in it, thus simplifying the algorithm workflow. Untari et al. [24] in their paper on modified back propagation algorithm employed the said algorithm for classification of follicles. They also presented the Levenberg-Marquardt Optimization and Conjugate Gradient- Fletcher Reeves; however the above methods gave better results than the modified Otsu technique but consumed more time. An automated approach for distinguishing between benign and malignant tumours was introduced by Acharya et al. [25] and Hu invariant and entropy, followed by support vector machines were used for the overall process. Möhlig et al. [26] made use of decision trees algorithm for prediction of impaired glucose metabolism in women suffering from polycystic ovary syndrome. Eliyani et al. [27] carried out Probabilistic Rand Index (PRI) and Global Consistency Error (GCE) methods on a dataset of ultrasound images of ovaries to pre-process,denoise, extract features, and finally perform follicular segmentation, which in turn was done by using active contours to accurately compute the number of follicles and their diameter. Meena et al. [28] proposed a new technique involving NFRS (Neural Fuzzy Rough Set) implemented in ANNs by means of which classification and feature selection can be done together to obtain best results in predicting PCOS in women. Lawrence et al. [29] employed the linear discriminant classifier (determined by 10-fold cross validation), KNN and SVM to automatically differentiate between normal and polycystic ovarian follicle, and obtained accuracies 92.86 percent, 91.43 percent, 91.43 percent respectively. The classifier they developed used two features: the mean and standard deviations and the proximity of the centroids of the individual follicles to the mean centroid. Sitheswaran and Malarkhodi [30] created a convex hull of possible follicles to search for most probable set of detections in the ultrasound images as follicles, thus making significant use of the spatial connectivity of follicles and the contour of the ovarian in which the follicles are nested. Srinivasan and Kumar [31] introduced the Improved Chan Vase (ICV) method (applied on despeckled images) against the Chan Vase (CV) method in order to get the best outcomes in feature extraction and classification of follicles with less iterations and computational time, as compared to the classical C-V algorithm. Kiruthika et al. [32] presented a new algorithm that used wavelet transform for denoising and k-means clustering technique for classification (based on intensity values), segmentation and fusion of the ultrasound images. Deng et al. [33] proposed a new automated system that uses watershed algorithm during the preprocessing phase and the object growing algorithm during the follicle identification phase for diagnosis of polycystic ovary syndrome (PCOS) . This was applied on 31 ultrasound images associated with PCOS and returned with a recognition rate of 89.4 percent. Abdullah et al. [34] presented the improvised thresholding based segmentation with inverse technique (TsTN) in attempt to partition natural images over other methods such as Otsu and K-means algorithm. The said TsTN method can be used as a possible image segmentation process over other existing algorithms in diagnosis of PCOS. Canny edge detection method is seen to be applied in the paper presented by Gopalakrishnan and Iyapparaja [35] for follicle edge detection. Also, the SIFT algorithm was successfully used for identification of the syndrome itself, followed by robust Machine Learning algorithms such as SVM, Naïve Bayes and Decision Tree. [Table I]

III. RELATION BETWEEN PCOS AND GENETICS

Polycystic Ovary Syndrome (PCOS) has long been speculated to have a genetic background to it. The affirmation of only one single gene being the causative force behind the occurrence of PCOS has not yet been established. This is partly due to various factors, such as the lack of a globally accepted clinical plan for PCOS, diagnostic ability only in women of reproductive age, limited number of patients in case-control studies, only one Or analysis of variants of two candidates and incomplete knowledge of the Patho-Physiology of the syndrome. [36]. A recent study by Lunde and colleagues showed that 19.7 percent of the first-degree male relatives of affected subjects experienced early baldness or excessive hair loss. 31.4 percent were affected for female first class relatives.

Sl. No.	AUTHORS	Approach	PERFORMANCE METRICS
1.	Sitheswaran and Malarkhodi, 2014 [30]	Enhanced labelled Watershed algorithm	F1 score : 88 percent
2.	Lawrence et al., 2007 [29]	LDC, KNN and SVM	Accuracy: 92.89 percent, 91.43 percent, 91.43 percent respectively.
3.	Hiremath and Tegnoor, 2010 [22]	Contourlet transform and Gaussian Low Pass filter	Accuracy: 75.2 percent and 62.3 percent respectively.
4.	Thufailah et al., 2010 [20]	Elman Neural Network (based on 32 features)	Accuracy: 78.71 percent
5.	Untari et al., 2016 [24]	Levenberg Marquardt and Conjugate Gradient-Fletcher Reeves	Accuracy: 93.925 percent and 87.85 respectively
6.	Meena et al., 2015 [28]	Naïve-Bayes and Artificial Neural Network with NFRS as feature selector.	Accuracy: 83.70 percent and 82.75 percent respectively

TABLE I: Listings of some notable papers

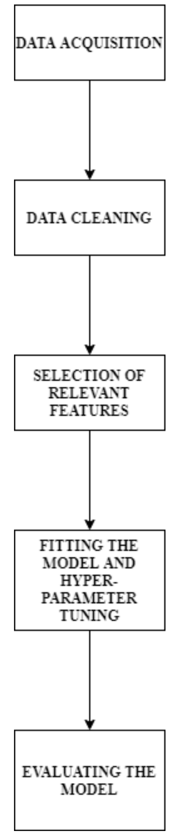


Fig. 1: Workflow of the model

Autosomal dominant inheritance can be excluded as an explanation of Polycystic ovaries in their entire data set, but their findings were consistent with this mode of inheritance for a large fraction of families. That study also discarded the possibility of X-linked inheritance. Because PCOS is an asymmetric disorder, it does not appear that it is caused by a single gene defect. Conversely, Polygenic inheritance or a combination of genetic and environmental factors may better explain the complex nature of PCOS, which leads to diagnosis by its treatment and determination of a stable cure. [37]

IV. PROPOSED METHODOLOGY

In the following sections, we make an attempt to present and break down the novel pedagogy in the form of an architecture we have designed in detecting if a patient in question is likely to have Polycystic Ovarian Syndrome. The most instrumental stage of this methodology was to determine and select the features which were the most important to the target value we selected which was the binary output column, PCOS (Y/N). We have also tried to schematically chart out our methodology in the form of a flowchart in figure 1 for our readers to have a better understanding and clarity of our model. In our line of research, after fixating on the input parameters, we selected the best model fit for our dataset and accordingly fine-tuned the hyperparameters to build a state of the art model and hence make the outcome as accurate as possible, both medically and statistically.

A. Data Acquisition

The progress that has happened over the last decade with regards to open source databases and also making databases open source is nothing short of remarkable. Today, one can easily go on to various repositories such as UCI Machine Learning Repository and Kaggle and find datasets of their choice. One also has the option to go to medical data repositories such as Physionet.org, if one's line of research strictly demands biomedical data. Alongside the fact that the datasets posted in these aforementioned repositories are readily available, they are mostly reliable as well, but it is always good practice to verify the data before starting off an analysis with the same.

The dataset we have used was collated from several hospitals in the city of Thrissur, Kerala. It is a combination of two datasets one with and another without infertility data. The dataset without infertility data had 5 rows x 43 columns, while Regardless of the fact that the dataset contained some null values and discrepancies, we found it to be a really good fit with the analysis architecture we had thought of previously. It contains medical data of 541 patients relevant to our detection mechanism to predict if a patient has PCOS or not. The dataset was found to be unbiased with regards to race, ethnicity, age and also other physical and clinical attributes of the patients. Compared to other PCOS ultrasound image datasets, we found this dataset to be the most reliable as this data was devoid of the effects of noise that are generally seen in medical image datasets collected over a prolonged period of time; this highlights our motivation behind selecting this particular dataset.

B. Data Cleaning

In this process, we first incorporated a method to find out the missing values and identify the columns which contained these values. After this step, we observed that in the dataset containing data without infertility the columns namely, Marriage Status (Yrs) and Fast food (Y/N) contain missing objects or entries; we filled the same with the corresponding median values in the respective columns. While at this stage, we also noticed that there was another column in the dataset which manifested only NaN values, which was 'Unnamed: 42', so needles to mention, we had to drop the same before we moved onto the next stage of our workflow. At this stage, we found out that after dropping the irrelevant columns and cleaning, our dataset had 4 rows x 42 columns. Compared to the first, the second dataset which contained data with infertility, was found to be relatively much cleaner and no null entries or objects were found or reported. Thus, after cleaning and checking for null objects, we merge the two datasets on the basis of the column 'Patient File No.'(which is common to both the datasets), so that the symmetry of the datasets are not lost and the consistency of data in the merged dataset is maintained.
We charted out the features which were the most important for the functioning of our model, using various statistical visualisation tools such as a correlation matrix, and scatter plots to observe if any two or more columns in our merged dataset are dependent on each other; and if they are correlated somehow, then we attempted to infer the extent to which they are correlated. Next, we dropped out the features or columns which were not at all related to our target column (PCOS (Y/N)) as mentioned above; as they would have had very minimal or no effect on the workflow of our model. We decimate the complexity of the process with this endeavour, by reducing the number of input parameters the user has to enter. After rigorous investigation, we decided on the finalized set of parameters and we have also included the same, later in this paper. Next, after fixating on a set of parameters, we then mapped out various kinds of plots with the chosen parameters against our target column, separately. In this section of our paper, we have tried to explain and interpret the schematics we obtained using a plethora of statistical methods and representations; taking into consideration four of the features which had relatively the strongest correlation with our target column.

C. SELECTION OF THE MOST RELEVANT FEATURES

These 32 features are chosen on the basis of extensive research carried out on the distinct peculiarities that are discerned in women experiencing PCOS. Majority of PCOS patients have increased Body Mass Index(BMI) along with weight gain, which is considered as a key factor in the diagnosis of PCOS (approximately about 40 percent-80 percent of the women having PCOS are obese). Now while recognising these parameters we stumbled upon one more criterion frequency of consumption of fast food. This is one of the most crucial features of our model as it is directly related to BMI. Higher BMI heads to larger waist size and hip size, manifests a higher waist to hip ratio. It was established that women with a waist to a hip ratio higher than 0.85 are mainly considered as potential targets of PCOS [38].
The table II displays those 32 features. Finalized feature table Research shows that 5 percent to 10 percent of the entire female population of the world is prone to get diagnosed with PCOS within the age group of 18 to 44. This made us include weight gain in our model as it is one of the easiest to be measured among the external characteristics of a human being.
Thyroid-stimulating hormone(TSH) performs a vital role in monitoring the metabolism and the reproductive system of our body. TSH is a hormone produced in the pituitary gland of the brain. Insufficiency of this hormone might affect the ovaries and thereby threaten fertility. It is increasingly being recognised that PCOS patients have thyroid disorders too. Although subsequent development of PCOS and hypothyroidism are two quite different diseases, they have several features in common i.e increased levels of thyroid-stimulating hormone (TSH). We found out that TSH levels higher than 4.5 mIU/ml are considered to be a matter of concern.
Luteinising hormone (LH) and follicle-stimulating hormone(FSH) are the main hormones associated with ovulation. These two are secreted from the pituitary gland of the brain. LH stimulates an egg to develop and FSH leads the egg to be released by the ovary in a process called ovulation. Elevated luteinising hormone to follicle-stimulating hormone ratio is considered to be a credential indicator of PCOS. In a survey, it was found that 60 out of 85 PCOS patients were having elevated levels of LH-FSH [39]. LH-FSH ratio greater than 2 is marked as the threshold for PCOS detection.
Anti-Mullerian Hormone (AMH) belongs to the transforming growth factor-beta superfamily. It plays a dominant role in the evolution and maturation of follicles. AMH in the bloodstream stays unaltered during the menstrual cycle. Use of contraceptives also doesn't alter its level. Thus increased levels of AMH is regarded as a clear indication towards PCOS. Patients with higher levels of AMH, i.e, greater than 4.45 ng/ml have 9.35 times increased possibility of having PCOS.
The rapid growth of body and facial hair can occur under the influence of hormonal imbalance. This hair growth takes place in the androgen-sensitive areas of the human body i.e upper lip, chin, chest and back. Hirsutism is a common feature among PCOS patients as told by the gynaecologists whom we consulted during the evaluation of our model. Discolouration and thickening of the skin are

TABLE II: Finalized feature table

Feature values determining PCOS		
Sl no.	Feature names	Thresholds for governing PCOS
1.	Body Mass Index	Greater 24(normal) lesser than 24(maybe are signs of being infected)
2.	Age	Ranges from 18 to 44 years
3.	Hair loss	Yes/No
4.	Skin darkening	Yes/No
5,	Pregnant	Yes/No
6.	Weight	40-80
7.	LH/FSH ratio	¿2(abnormal) otherwise(normal)
8.	Blood group	A+, A-, B+, B-, O+, O-, AB+, AB-
9.	Respiration Rate (breaths/min)	Normal/Abnormal
10.	Pulse rate(bpm)	High/low
11.	Measurement in hip size	large/medium/small
12.	Measurement in waist size	large/medium/small
13.	Waist-hip ratio	¿0.85(Abnormal) /otherwise(Normal)
14.	Miscarriage or early loss	Yes/No
16.	Thyroid stimulating hormone	¿4.5(mU/lit.)(abnormal ¡otherwise(normal)
17.	Anti mullerian hormone levels	High/low
18.	Prolactin levels	HIgh/low
19.	Vitamin D3 level	High/low
20.	Hair growth	Yes/No
21.	Skin darkening	Yes/No
22.	Diabetes(before and after food)	Normal/Abnormal
23.	Fast food Consumption	Yes/No
24.	Weight gain	Yes/No
25.	Acne	Yes/No
26.	Routine Exercise	Yes/no
27.	Blood Pressure Systolic	High/normal
28.	Blood pressure diastolic	High/normal
29.	Follicle number per ovary	Normal/Abnormal
30.	Average follicular size	Normal/Abnormal
31.	Thickness of Endometrium	High/Low
32.	beta human chorionic gonadotropin levels	Normal/Abnormal

noticed in the PCOS victims, the skin turns to black or dark brown with a velvety texture. These patches of skins are associated with a condition known as acanthosis nigricans. Thus, it is considered as a good indicator to show endocrine disorders.

Along with infertility PCOS brings in hormonal imbalance leading to various problems in the human body. The body depends on the pituitary gland to secrete the right amount of hormones like estrogen, progesterone and testosterone which leads to various dysfunctions in the female body. One of the most evident symptoms is acne, especially in pubescent patients. Thus the presence of acne in the women in their adolescent and birth-giving years is considered as an indicator of PCOS.

The number of miscarriages and abortion can affect a female reproductive system making them vulnerable to PCOS.

PCOS is closely associated with various contingency factors related to cardiovascular disorders. In a survey, 243 PCOS subjects with unknown factors of cardiovascular disease went through a cardio-pulmonary exercise test for the measurement of heart rate in breaths per min and blood pressure. 89 patients were found with a respiratory rate higher than 18 who when diagnosed were found to have higher risks of having PCOS. Thus respiratory rate higher than 18 breaths/min indicates the presence of this endocrine disease [40].

In the above-mentioned age window, menstrual abnormalities can indicate PCOS in women. Prolonged or delayed periods show a direct correlation to PCOS. The magnitude of impact offered by this parameter is approved by professional gynaecologists which made our model more robust and authentic. Heavy androgen content and excess insulin in the body of a female meddles with the monthly menstruation cycle. In a survey, it is noticed that out of 205 PCOS patients 144 have noted shifts in the pattern of their menstruation cycle. Out of the 144 subjects, 137 had restricted menstrual cycles and others had a longer than usual cycle [41].

About 15 to 20 follicles mature for ovulation every month in the ovary. The elevated volume of androgen in the bloodstream doesn't let any follicle to completely mature, leading to the formation of cysts. These cysts transpire to be the main contributor to androgen regulation in the human body. Thus the rising number of follicles is a concrete indicator of PCOS in women.

D. FITTING THE MODEL AND HYPER-PARAMETER TUNING

The most crucial parameters that were selected from the above selection processes were recognized and considered according to their priority. Certain features along with 541 instances are selected and saved under one common label name and the resulting PCOS condition is saved under a target name.

These two labels are split into two separate datasets for training and validation. We have used the scikit-learn library for splitting the data. 80 percent of the data was taken for training and the remaining 20 per cent for testing. This allocated 432 training and 109 testing instances from the dataset. The training set was then fed into various machine learning algorithms to learn and categorize the PCOS and non-PCOS patients into two separate classes. This training sub-part of the data is used to make the computer understand the several patterns depending upon the supreme features put together, with the help of extensive statistical circumspection. We have then used this prepared model on the evaluation set to conclude the performance of our model based upon the testing accuracy, precision and recall of the evaluation data. The Machine Learning algorithms used are Logistic Regression, Random Forest classifier, Gaussian Naive Bayes classifier, Ridge Classifier, Linear Discriminant Analysis, AdaBoost Classifier, k-Nearest Neighbours Classifier, Decision Tree Classifier, Gradient Boosting, Gaussian Process Classifier and Support Vector Machine Classifier.

The fitting of the model with the training labels and targets gives the system the capability to learn the statistical patterns from the training data. By virtue of hyperparameter tuning these classifiers gain the ability to classify better from the provided data. Now hyperparameter tuning for distinct classifiers is unique in their own way.

The Random Forest classifier was ascertained to be single most suitable classifier from the enormous repository of classifiers that we have used in our model training. Now the hyperparameters that were tuned to get the respective evaluation results are given below.

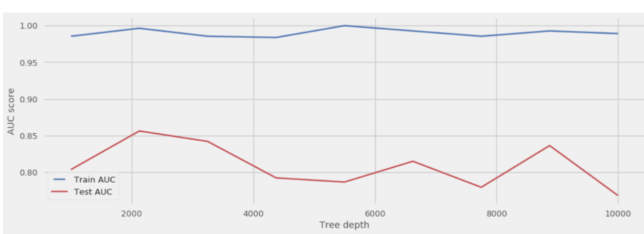


Fig. 2: Representation of the AUC score with respect to the depth of the tree.

max_depth gives a notion about the depth of the trees in the random forest classifier. The deeper the trees, the greater the number of splits will resemble, enabling our classifier to make more decisions and exposing our data to more circumstances of tweaking the prototype's decision-making accuracy. In our model 2200 was taken as the max_depth value. The graph fig 2 depicted above shows the association of AUC with max_depth. n_estimators are the number of trees that are built within a Random Forest before the evaluation of predictions. The higher the value of n_estimators the better, only if the computational expenses and processing speed can be compromised. Here we have

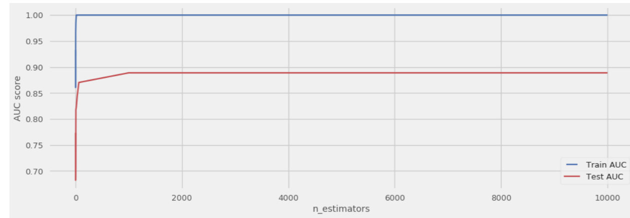


Fig. 3: Representation of the AUC score with respect to the n_estimators parameter

selected 9000 to be the n_estimators value. The preceding graph fig 4 shows the relation of AUC with n_estimators.

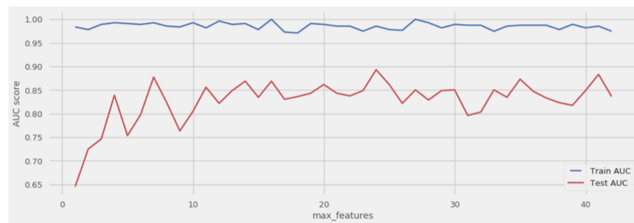


Fig. 4: Representation of the AUC score with respect to the max_features parameter.

The max_features parameter can either be a float, an integer, a string, or just None. Just like n_estimators, the larger the value of max_features the better, for it gives information about the number of features considered when finding the best split in the model. A greater number of features results in improved performance but reduces the computational time. In our model, we took 0.3 as the max_features. The following graph fig 5 shows the relation of the AUC with max_features. min_samples_leaf : min_samples_leaf gives

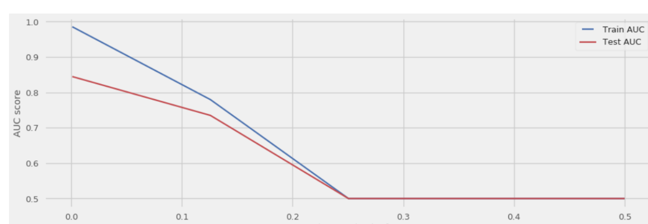


Fig. 5: Representation of the AUC score with respect to the min_leaf_samples.

an account of the number of samples that are required to be at the leaf node; it is another metric that controls the depth of the tree and thus enhances the performance of the classifier. Tuning this parameter shows its best results at 0.001 min_samples_leaf value. The following graph shows the relation of AUC with min_samples_leaf.

E. COMPARATIVE ANALYSIS BETWEEN CLASSIFIERS

Based upon the binary nature regarding the data we can ascertain that this is a classification problem. The ones and zeros expose the presence and absence of this ovarian disease. We have used a total of 10 classifiers on this data. The precedence of the classifiers is circumscribed by how significant results can these classifiers render. The measurement tools providing the scale of results given are evaluation accuracy, precision, recall, specificity, sensitivity, AUC score, etc. These classifiers are further fine-tuned to give higher decisive scores. This fine-tuning is done by modifying the hyper-parameters of the classifiers. The classifiers used are further decreased to 4 major ones. : Logistic Regression, Random Forest classifier, AdaBoost Classifier, Gradient Boosting.

- **True Positive**

is the type of outcome from the model that correctly predicts the positive value. For example, It rained today (if, say, rain is a positive value). The notation here is affirmative hence the outcome is termed as true positive.

- **False Positive**

is the type of outcome from the model that incorrectly predicts the positive value. For example, No sunshine today (if, say, sunshine is a negative value). The notation here is negative of a positive event and hence the outcome is termed as false positive.

- **True Negative**

is the type of outcome from the model that correctly predicts the negative value. For example, It did not rain today. The notation here is affirmative for a negative event.

- **False Negative**

is the type of outcome from the model that incorrectly predicts the negative value. For example, There was sunshine today. The notation here is negative for an incorrect value.

Confusion matrix : The composition of correct and incorrect predictions in tabular form is known as the confusion matrix. This matrix simulates insights from the evaluation of our classifier model. The exact errors can be picked out from the types of mistakes made by the classifier, depicted in the confusion matrix. The representation of the same is described below IV-E.

actual value	**Prediction outcome**		
	p	**n**	**total**
p′	True Positive	False Positive	P′
n′	False Negative	True Negative	N′
total	P	N	

Precision: Precision denotes the percentage of the outcomes that are relevant. It is given by the formula:

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

Higher the precision score is lesser the number of false positives.

Recall:

Recall, also known as Sensitivity, gives the account of the total relevant results correctly identified/classified by the algorithm.

It is given by the formula :

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives}$$

Higher the recall score is fewer the number of false negatives.

Accuracy:

Accuracy gives the measure of how well the employed algorithm is working on the model, or how well a classifier correctly buckets the classes according to the learning parameters.

$$Accuracy = \frac{TruePositives + FalsePositives}{Total}$$

AUC score:

AUC (Area under the Curve) score is used to determine which of the deployed models is the best at classifying the classes, and ranks all of them accordingly. AUC ranges from 0.0 to 1.0. In our model, the best AUC score was accomplished by the Random Forest classifier, at 97.0

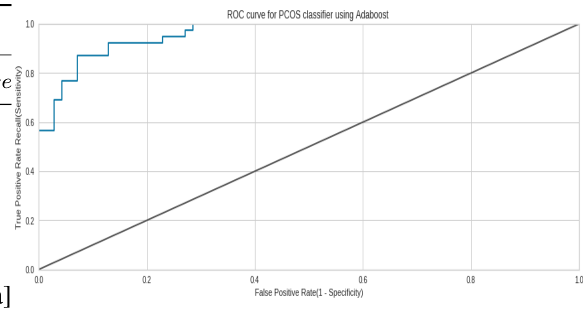
F1 score:

F1 score is represented as the harmonic mean of the precision and recall of the test data of the model. In case of uneven class distribution(as in the data used in our model training), the F1 score is considered to be more important than accuracy. Just like the AUC score, the best F1 score was also given by Random Forest, at 94.0

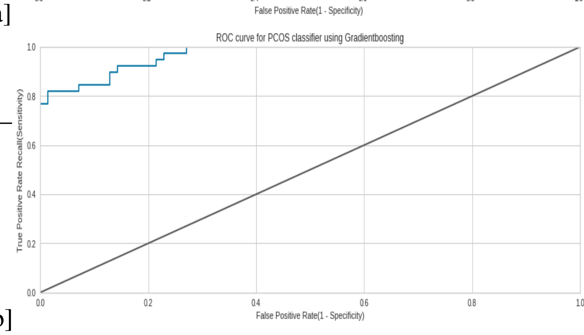
$$F = \frac{Precision \times Recall}{Precision + Recall} \times 2$$

Classifier	Evaluation metrics					
	Test Accuracy	Precision	Recall	Specificity	AUC$_{s}core$	F1$_{s}core$
Random Forest Classifier	92	93	92.9	89.4	97	94
Adaboost Classifier	89	89	87	90	95.8	87
Linear Discriminant Analysis	85.3	86	86.4	82	95	83.5
Gaussian Naive bayes	81.6	82.5	80.4	85.18	84.1	78.5
Gradient Boosting Classifier	88	86.90	91.3	82.5	96.8	87.5
Logistic Regression	90	89.5	91.5	86.8	93.3	89
Decision Tree Classifier	80.7	81.5	87.6	70.4	80.4	79.5
Ridge Classifier	86.23	86.6	85.71	87.5	-	84.5

TABLE III: Table caption text



[fig 6.a]



[fig 6.b]

Fig. 6: AUC-ROC curves of Adaboost and Gradient Boosting classifier

Among the classifiers used Support Vector Machine performed the worst with the lowest test accuracy of 64.22 percent. The confusion matrix that we acquired from this classifier gave some very unusual results. The false negatives score or the type 1 error was detected to be quite high that held about 35 percent of the evaluation instances. That might be a problem as this many percents of the patients are being diagnosed with PCOS. The precision, recall and F1 score found were very low showing 32 percent, 64 percent, and 50 percent respectively.

In the Gaussian Naive Bayes Classifier, the accuracy score acquired from the test results was 81.6 percent. The precision and recall score is 82 percent and 76 percent respectively. This classifier has predicted 16 false negatives and 4 false positives, that shows ambiguity in the results meaning false predictions thus this classifier is left out.

The confusion matrix obtained from the Ridge Classifier has been given below [[66 4] [11 28]] It can be concluded from above that this classifier has generated a relatively larger number of false negatives, which is not desirable. It also gives an overall test accuracy of 86.23 percent. This might give erroneous diagnosis results and false predictions and so this classifier has not been considered in our top evaluations.

Lastly, the k-Nearest Neighbours classifier gave a test accuracy of 66 percent, with 62, 55 and 52 percent as precision, recall and F1 score respectively. This performance can be deemed to be very poor compared to the rest, and upon observing the confusion matrix, we see that the number of false negatives is also huge (32) along with 5 false positives, making this classifier unfit for our PCOS diagnostic evaluations. booktabs fouriernc

V. RESULT ANALYSIS

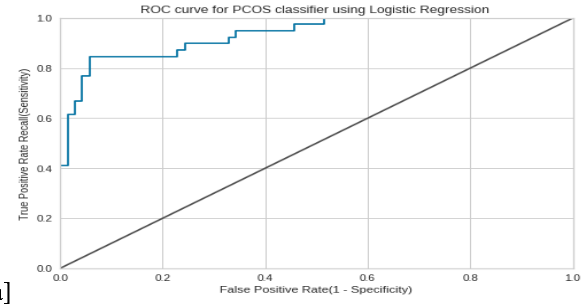
1) **AUC-ROC curve representation of the four best classifiers :**

From the AUC-ROC curve fig 6.(a) obtained through the Adaboost classifier evaluation, it is seen that the true positive rate is going lower than 0.6 which is not desirable but it nearly balanced out by the False Positive Rate (1-Specificity) and ultimately an AUC score of 95.8 per cent is achieved thus making Adaboost the The Gradient boost classifier performs nearly as well as the Random Forest classifier in terms of AUC score, obtaining 96.8 percent. This result can be attributed to a lesser false positive rate and the true positive rate which can be inferred from the curve plotted in fig 6.(b).

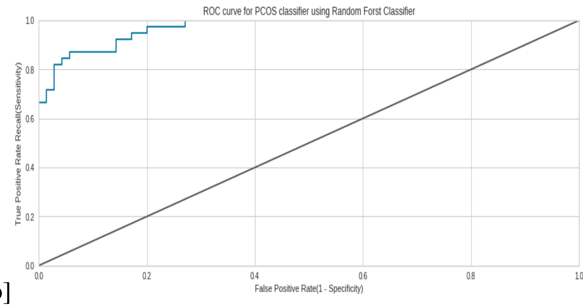
Out of the four classifiers described here, logistic regression performs the least in accordance with our desired goal based on the AUC score (93.3 per cent in case of logistic regression). Compared to the rest, this classifier has a significantly higher False Positive rate, resulting in the depreciation of its AUC score. The curve of this classifier's AUC score is the fig 7.(a).

The AUC score obtained from the Random Forest Classifier is 97 percent. This score shows and proves the capability of our model to classify and detect PCOS. A genuine measure separability of the data is established here in the curve (fig 7.b).

Specificity and sensitivity are two parameters which are inversely proportional to each other; increment of one results in the decrement of another. The AUC-ROC curve above depicts the relationship between these two evaluations matrices, which is displaying some small amount of type 1 (False Positive) and type 2 (False negative) error. The insignificant amount of these errors prove the confusion matrix formed erstwhile with the predicted results. Sensitivity value from an evaluation result shows how perfectly the model has been able to diagnose patients who have PCOS and that the classifier has been able to identify 89.4 percent of the patients with the syndrome. Determining the specificity of any classifier can prove to be very beneficial in ruling out the disease if a



[fig 7.a]



[fig 7.b]

Fig. 7: AUC-ROC curves of Logistic Regression and Random Forest Classifier

person tests negative for it, but will return a false-negative result for the remaining 10.6 percent. The specificity of a test gives an estimate of the patients without PCOS who have tested negative for it. According to our model, 92.9 percent of the subjects have been identified to not have the syndrome. In contrast to sensitivity, the specificity of a model can prove to be advantageous in ruling out people when they have this disease. Now further when this trained model was being implemented on a test set to make predictions it gives a fixed number of true positives, true negatives, false positives and false negatives were derived, the representation of which is given the chart below.

actual value | **Prediction outcome from 109 patients**

	p	**n**	
p′	66	4	P′
n′	5	34	N′
total	P	N	

2. ***Further Analysis***

The best performing classifier in our model was Random Forest, and the visualisation obtained from the same has been displayed above. The first parameter preferred here in one of the instances upon which the decision was to be made was the ‘Weight Gain’ metric with a threshold value of 0.5, and based on this value the propagation was carried onto either ‘Hair Growth’ or ‘FSH/LH’, and so on. This basically signifies one of the decision trees in the Random Forest classifier evaluated on our model. The following graph Fig 8 depicts the decisions one of the Decision Trees of the Random Forest Classifier has taken to traverse through the tree. Now with subsequent computations, we

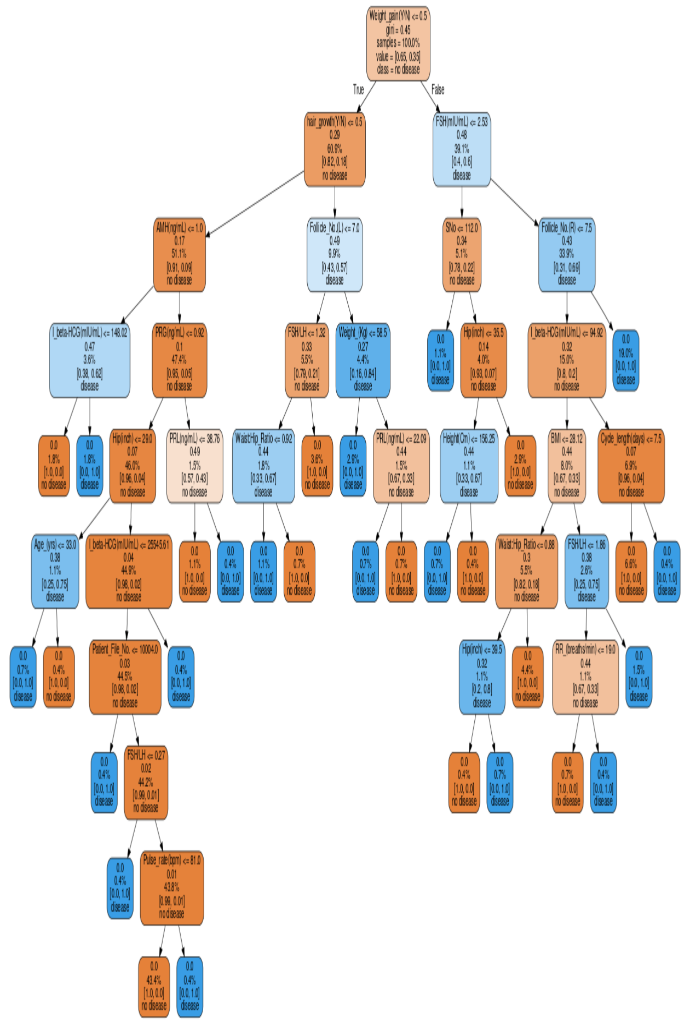


Fig. 8: Decision tree of a Random Forest Classifier

found out the precision and recall of Random Forest classifier. The precision we acquired is 91.2 percent and recall is 90.7 per cent, which shows that our classifier gave less number of False Positives as well as fewer False Negatives. The graph plotted below shows the precision-recall curve we obtained from our classifier. This graph Fig 9 represents precision and recall in the y-axis and x-axis respectively. The blue area in the graph shows the gradual precision and recall map of the Random Forest Classifier. The red dotted line represents the average precision score with the progressive increase recall. This area under the whole curve shows how the classifier has performed on the data, the larger the area under the curve the better. This classifier has high precision and recall thus the AUC is significantly large here. This infers Random

Forest Classifier is producing the best results among the other classifiers used in this dataset. This enables us to confirm that our model is robust and it efficiently classifies the data into specific respective groups of having or having PCOS.

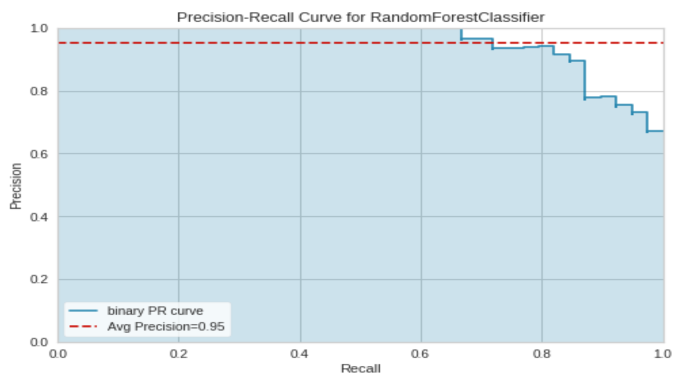


Fig. 9: Precision-Recall curve

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