

Analysis of the prevalence and health impact of [PCOD/PCOS] among women.

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1. ABSTRACT:

Polycystic Ovary Syndrome (PCOS), commonly referred to as Polycystic Ovarian Disease (PCOD), is one of the most prevalent endocrine and metabolic disorders affecting women of reproductive age. It is characterized by hormonal imbalance, menstrual irregularities, hyperandrogenism, and polycystic ovarian morphology. The condition has a significant impact on reproductive, metabolic, psychological, and overall health. This study aims to assess the prevalence of PCOD/PCOS among women and evaluate its associated health impacts. The analysis focuses on common clinical manifestations, including irregular menstruation, excessive hair growth, acne, weight gain, infertility, and metabolic abnormalities. PCOS is also associated with an increased risk of insulin resistance, type 2 diabetes mellitus, dyslipidemia, cardiovascular complications, and psychological concerns such as anxiety, depression, and reduced quality of life. Early identification and appropriate management through lifestyle modification, medical treatment, and regular monitoring can help reduce long-term complications. Increasing awareness among women and healthcare professionals is essential for timely diagnosis and effective management. Understanding the prevalence and broad health consequences of PCOD/PCOS can contribute to improved preventive strategies, reproductive health outcomes, and quality of life among affected women.

KEYWORDS: Polycystic Ovary Syndrome, PCOS, Polycystic Ovarian Disease, PCOD, prevalence, women of reproductive age, hormonal imbalance, menstrual irregularities, infertility, insulin resistance, metabolic health, mental health, quality of life.

INTRODUCTION

Polycystic Ovary Disease (PCOD), more accurately termed Polycystic Ovary Syndrome (PCOS), is a complex endocrine–metabolic disorder affecting women of reproductive age. The condition was first described in 1935 by Irving F. Stein Sr. and Michael L. Leventhal, who identified a cluster of symptoms including amenorrhea, infertility, hirsutism, and enlarged polycystic ovaries. Initially referred to as Stein–Leventhal syndrome, PCOS is now recognized

as a heterogeneous systemic disorder characterized by chronic anovulation, hyperandrogenism, and polycystic ovarian morphology. It is one of the most common causes of anovulatory infertility worldwide and is increasingly associated with metabolic complications such as insulin resistance, type 2 diabetes mellitus, Dyslipidemia, and cardiovascular risk.

The prevalence of PCOS/PCOD varies globally, largely depending on the diagnostic criteria applied and the population studied, but it is a significant public health concern:

Global Estimates: The global prevalence of PCOS/PCOD is generally estimated to range between 5% and 15% of women of reproductive age (15–49 years), with some estimates going as high as 26% depending on the diagnostic criteria used. **Undiagnosed Cases:** A major concern is the high number of undiagnosed cases; up to 70% of affected women worldwide may remain undiagnosed.

Indian Context: India carries a considerable share of this burden, with a pooled prevalence estimated to be

around 10% based on Rotterdam criteria in some studies. Regional studies have reported prevalence rates as high as 17.40% in specific urban areas, underscoring the severity of the issue in the country. In 2021, there were an estimated 65.8 million prevalent cases of PCOS/PCOD globally, with the burden increasing significantly over the past few decades.

Associated Complications: PCOS/PCOD is more than just a reproductive issue; it is a complex syndrome linked to a wide array of long-term health problems, which amplify its burden on individuals and healthcare systems.

Metabolic Disorders: It is strongly associated with insulin resistance (IR), type 2 diabetes mellitus, impaired glucose tolerance, obesity, and metabolic syndrome. Women with PCOS, especially those with hyperandrogenism, are about 2.5 times more likely to develop type 2 diabetes.

DATA COLLECTION

- **Target population:** Women in the age group 12-45 years.
- Data set consists of a total **260** sample Observations.
- Among **83** women diagnosed with PCOD/PCOS.
- **Prevalence assessment:** Questionnaires and physical examinations such as BMI, BP and signs of Hirsutism.
- **Data collection:** Collection of data (prescriptions)
- **Study Areas:** College, villages near by college, gynaecology hospitals.
- **Analysis:** Apply standard criteria to calculate prevalence and identify risk factors.
- **Diseases and complications:**
- **Reproductive issues:** Leading causes of infertility (anovulation) and irregular/absent periods
- **Metabolic syndrome:** High risk of insulin resistance, obesity and high BP.
- **Other impacts:** Increased risk of Anxiety and Depression.

METHODOLOGY

In this study, machine learning classification technique has been proposed, trained and tested aims to differentiate between PCOS and non-PCOS ovaries. The ovary disease variables have been used as the input of the study from which the suggested method would determine whether or not the women having PCOD/PCOS. Along with this we performed comparative analysis to identify which classification technique is well suited for our data. The framework of the methodology used in this research is illustrated below:

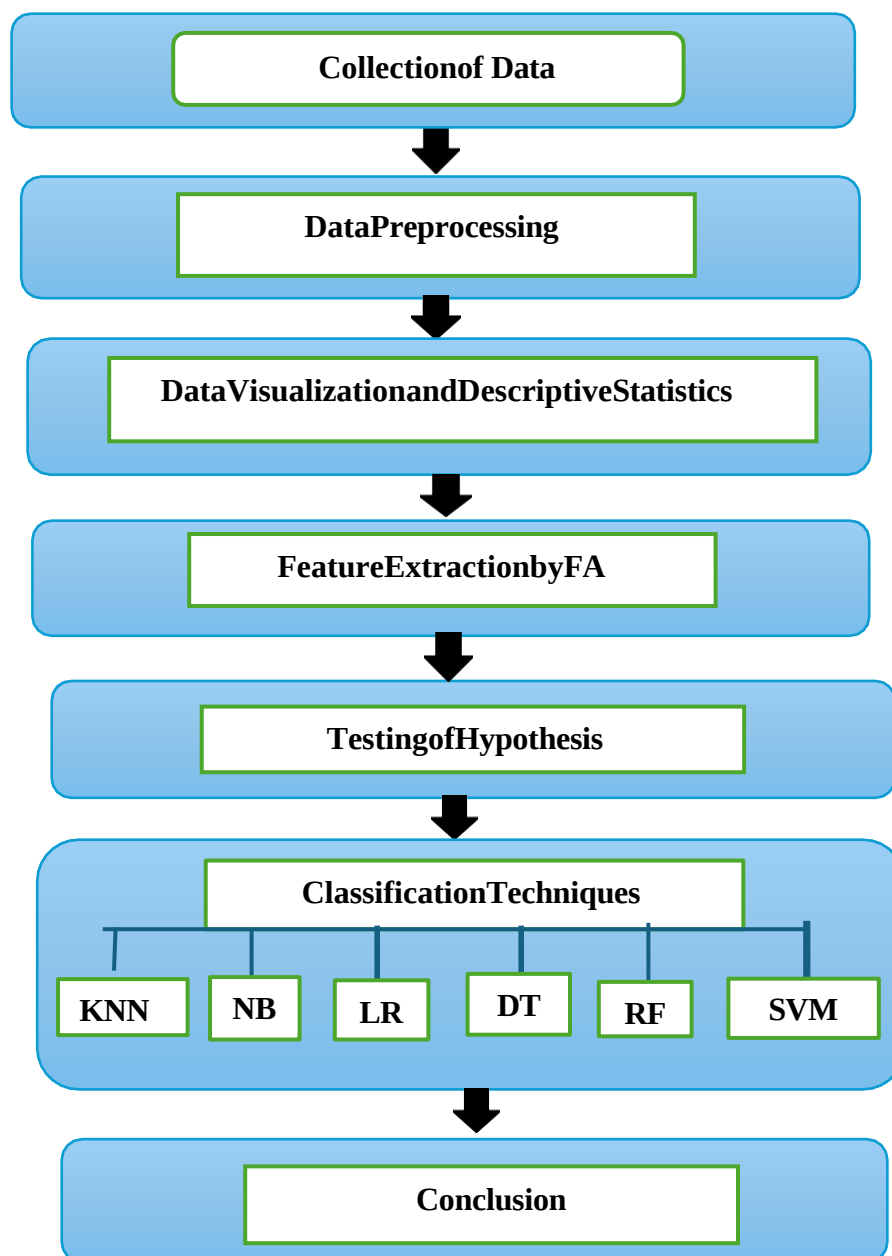


Fig.4.1:Methodology

STATISTICAL TOOLS

Exploratory Data Analysis:

- Barcharts, PieCharts, CorrelationHeatmap
- Chi-squaretest
- Feature Extractionby FA
- Classifications Report

Machine Learning Algorithms (DataMiningClassifiers):

- RandomForest,K-NearestNeighbourhood,NaiveBayes,SupportVectorMachine, Logistic Regression, Decision Tree.

Statistical Software:

MS-Excel



Python



GRAPHICAL REPRESENTATION

Table4.1:Menstrual cycle of irregular

Age group(years)	No.of women(irregular)
15-20	50
20-25	25
25-30	15
30-35	8
35-40	5

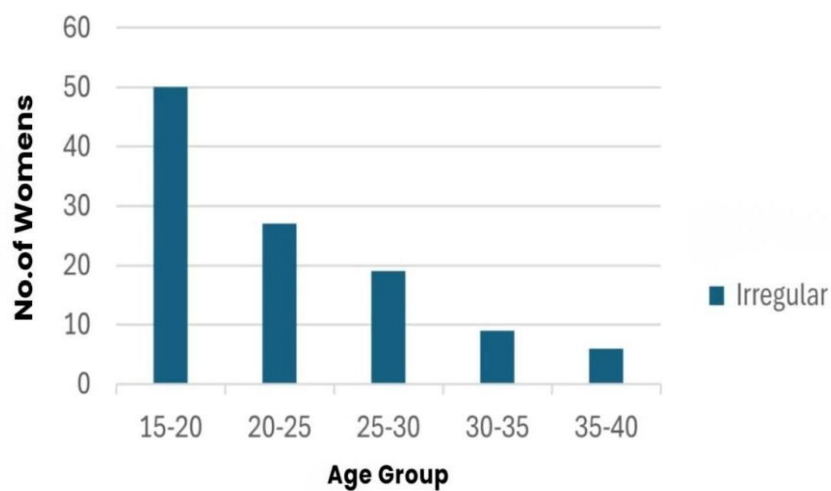


Fig.4.2:Graphical distribution of women with irregular menstrual cycles across different age groups.

Conclusion: Menstrual irregularity is most common in the 15-20 age group. The prevalence decreases gradually as age increases

Table4.2:Menstrual cycle of regular

Age group	No of women (regular)
15-20	44
20-25	83
25-30	15
30-35	4
35-40	1

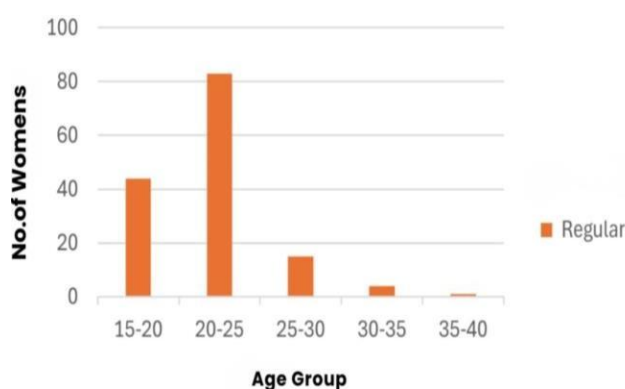


Fig. 4.3: Graphical distribution of women with regular menstrual cycles across different age groups.

Conclusion: The graph shows that regular menstrualcycles are most prevalent in the 20-25 years age group.

Table4.3:Menstrualcycleofirregularandregular

Age Group	Irregular	Regular
15-20	50	44
20-25	27	83
25-30	19	15
30-35	9	4
35-40	6	1

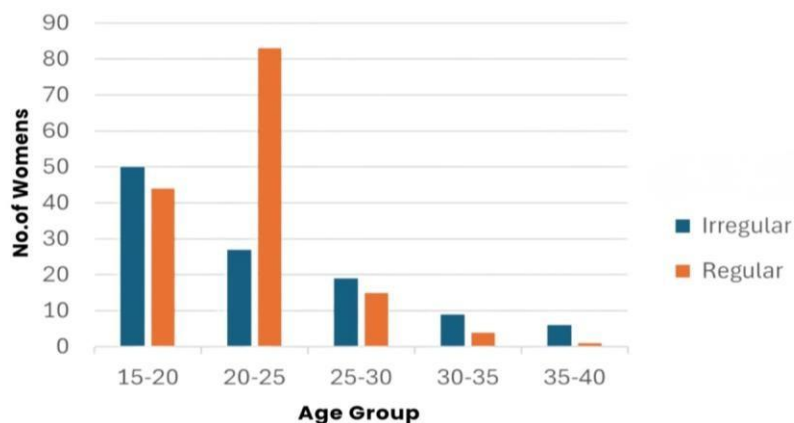


Fig.4.4: Graphical distribution of women with irregular and regular menstrual cycles across different age groups.

Conclusion: women aged 20-25 have the highest prevalence of irregular menstrual cycles. Regular cycles are more common in ages 15-20, with irregularities decreasing after 25

Table 4.4: Impact of BMI on PCOD/PCOS women

BMI Category	Irregular	Regular
Normal	50	90
Obese	8	6
Overweight	25	10
Underweight	27	20

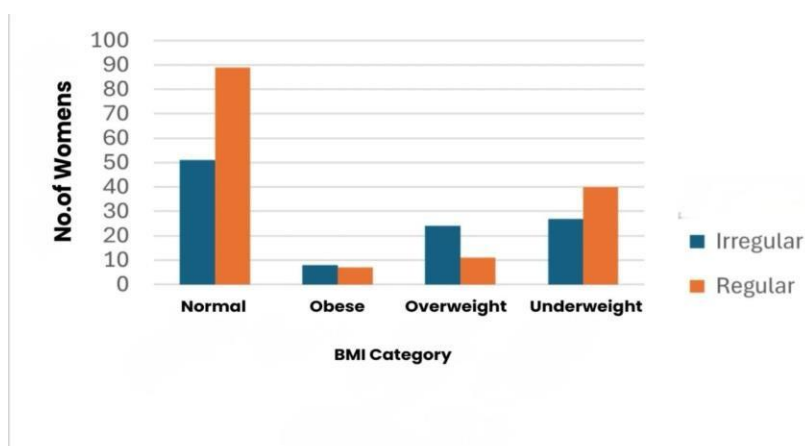


Fig.4.5: Graphical distribution of women with irregular and regular menstrual cycles according to different BMI categories.

Conclusion:Most PCOD/PCOS affected women are in the normal BMI category. Irregular menstrual cycles are more common among overweight and obese women.

Table4.5:Reasons behind PCOD/PCOS

Reasons	Number of cases	Percentage
Hormonal imbalance	31	37.3%
Eating Disorder	21	25.3%
Stress	19	22.9%
Others	12	14.5%

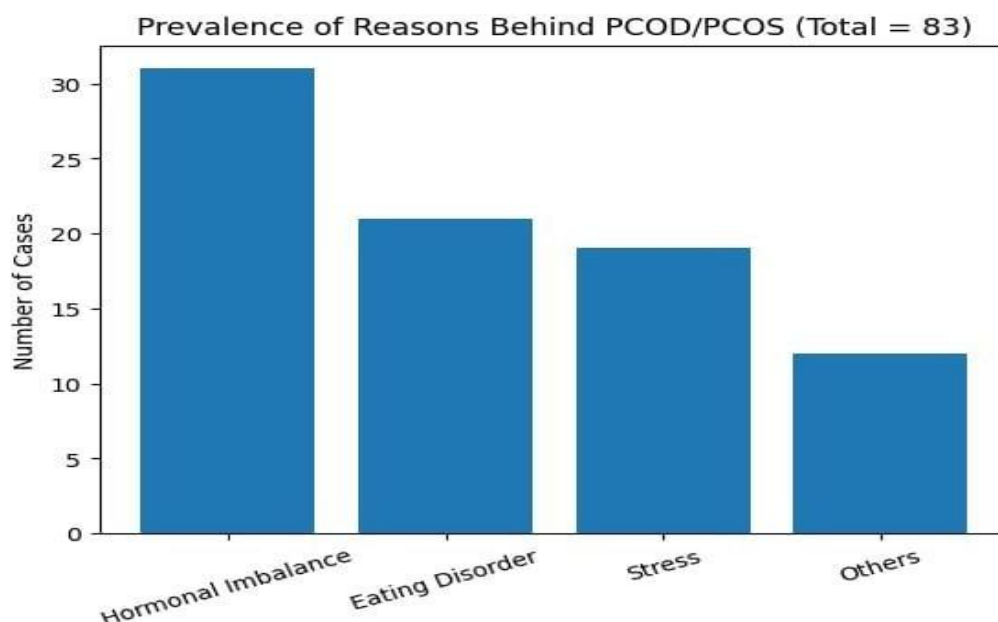


Fig.4.6:Represents the different reasons behind PCOD and the number of cases observed for each reason.

Conclusion:Hormonal imbalance is the leading cause of PCOD/PCOS, accounting for the highest proportion of cases (37.3%).Eating disorders and stress also contribute significantly, while other factors represent a smaller share

Table4.6:Day off low inPCOD/PCOS

Age group	2-3days	4-5days	6-7days
15-20	5	18	0
20-25	11	20	9
25-30	3	7	3
30-35	0	3	1
35-40	1	1	0

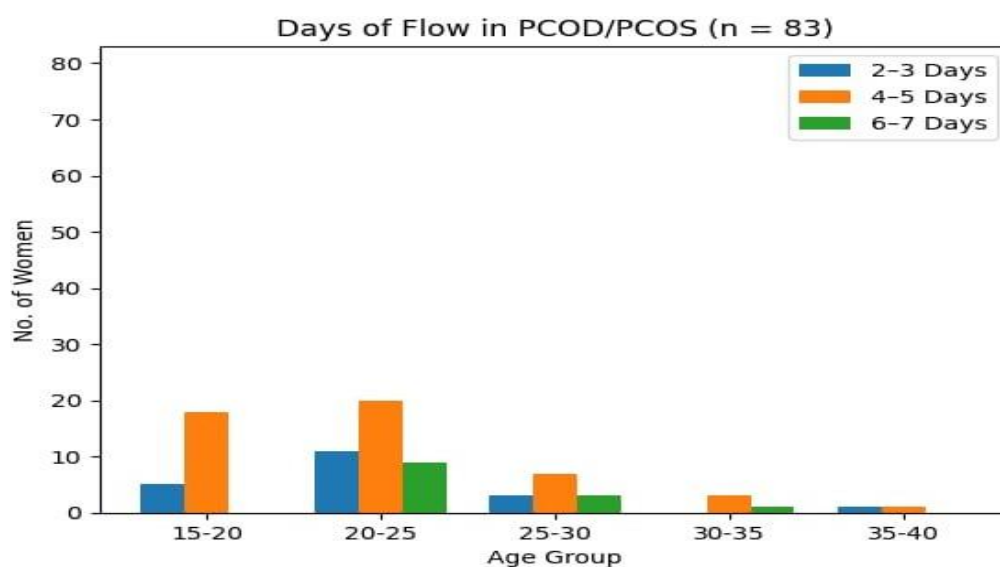


Fig.4.7:Represents therelationshipbetweenagegroupanddaysofmenstrualflowamong women.

Conclusion:MostwomenwithPCOD/PCOShave4-5daysofmenstrualflowintheagegroup 20-25.

4.7:Piechartofpregnancyproblem inPCOD/PCOSwomen

Response	Percentage
Yes	73%
No	27%

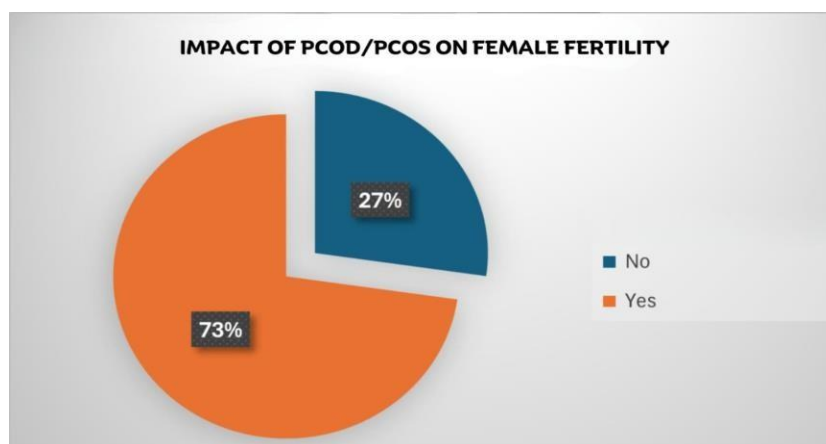


Fig.4.8:Represents the impact of PCOD/PCOS on female fertility.

Conclusion: It observed that 73% of women with PCOD/PCOS have experienced pregnancy problem.

Table 4.8: Pie chart of eating habit in PCOD/PCOS women

Dietary Pattern	No. of Women	Percentage
Fast food	30	40%
Balanced diet	26	30%
Oily/spicy foods	26	30%

Dietary Pattern Among 83 Women with PCOD/PCOS

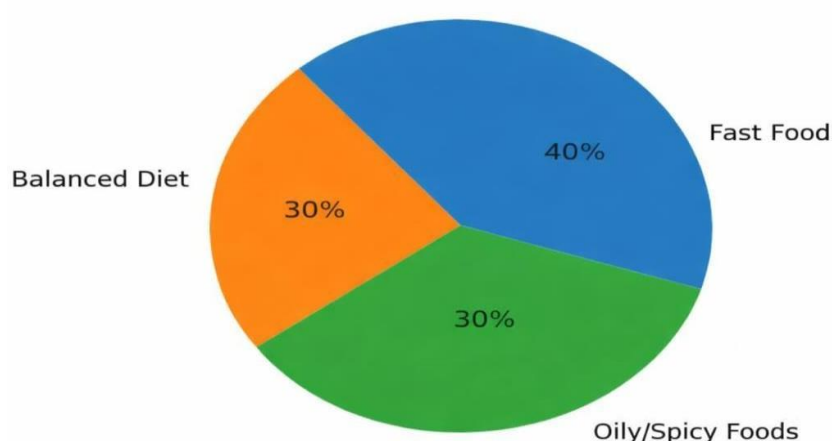


Fig.4.9:Represents the dietary pattern among women with PCOD/PCOS.

Conclusion: Most women with PCOD/PCOS (72%) follow a balanced diet. However, 28% consume fast food (11%) and oily/spicy foods (17%), which may negatively impact their condition

Table4.9:ImpactofPCOD/PCOSduringperiods

ProblemFaced	NoofRespondents
Noproblem	16
Backpain	30
Stomachpain	33
Legpain	4

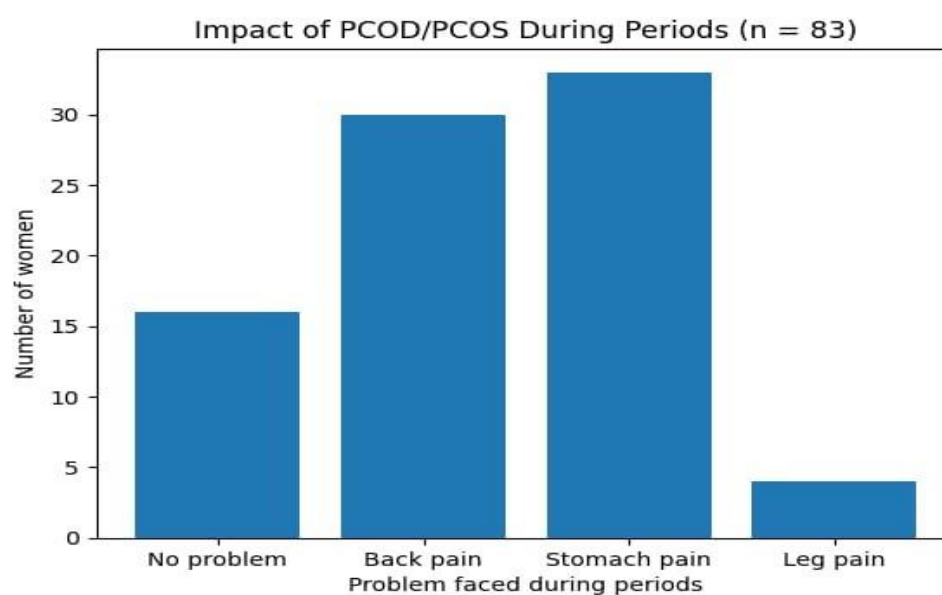


Fig.4.10:Represents the impact of PCOD/PCOS during periods among women.

Conclusion: Stomach pain (33) and back pain (30) are the most commonly reported problems during periods among the women. While leg pain (4) was the least experienced problem.

Table4.10: Comparison of Medical Approaches

Treatment type	No of Women
Allopathic	61
Homeopathic	22

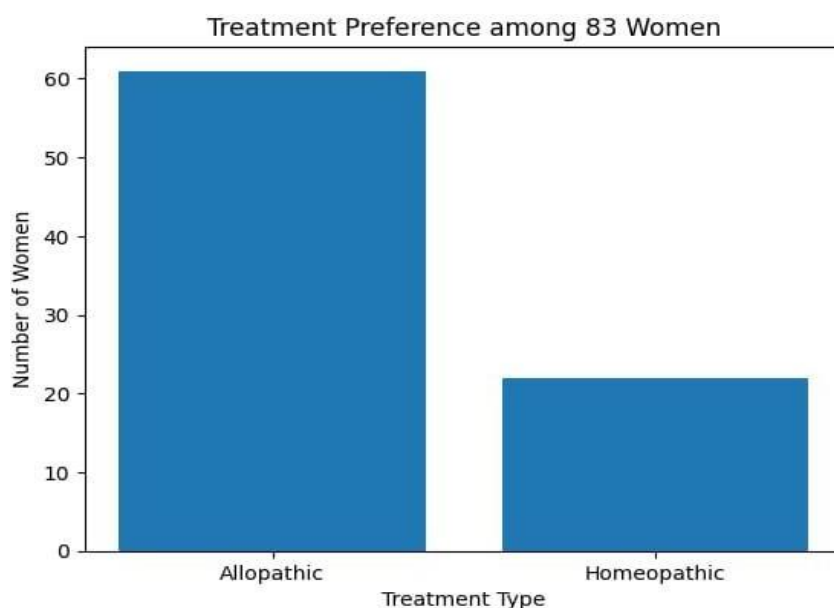


Fig.4.11:Represents the treatment preference among women with PCOD/PCOS.

Conclusion: The majority of women with PCOD/PCOS prefer allopathic over homeopathic treatment.

Table4.11:Urban and rural distribution of PCOD/PCOS women

Area	Percentage
Urban	74%
Rural	26%

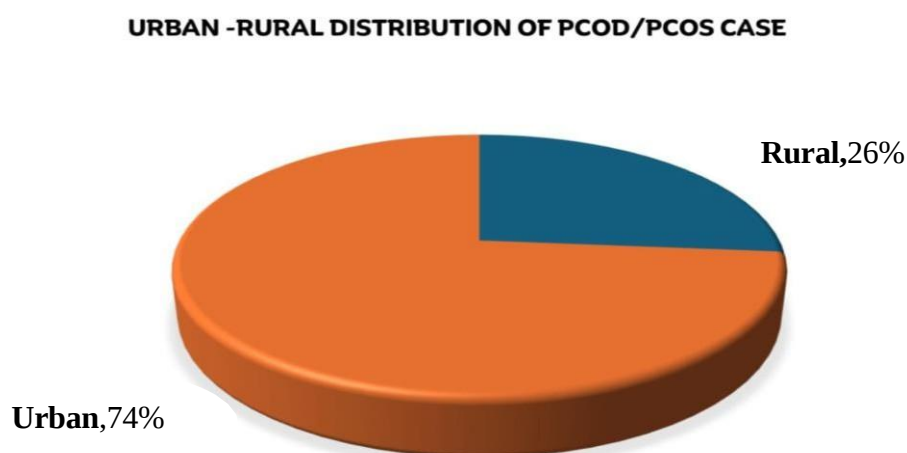


Fig.4.12:Represents the urban–rural distribution of PCOD/PCOS cases.

Conclusion:Urbanareashowsahigherprevalenceof PCOD/PCOScaseswith106cases [74%] compared to rural areas with 38 cases [26%].

Table4.12:FoodhabitpatterninPCOD/PCOSwomen

FoodHabit	NoofWomen
Vegetarian	20
Non-vegetarian	10
Both	228

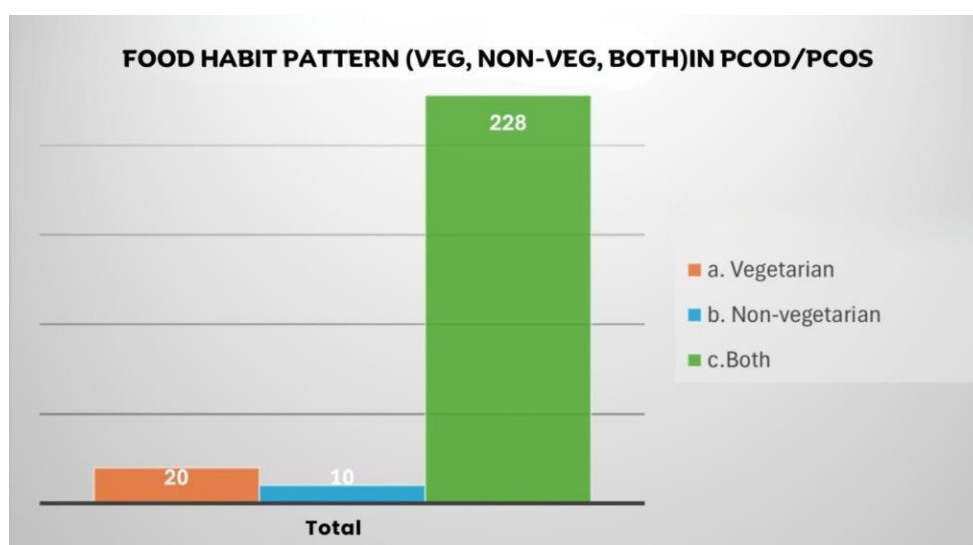


Fig.4.13:Representsthefoodhabitpattern.

Conclusion:Thegraphindicates thatthemajorityofPCOD/PCOS casesareassociatedwitha mixed diet pattern.

Table4.13:MaritalstatusamongPCOD/PCOSwomen

Maritalstatus	Percentage
Unmarried	79%
Married	21%

MARITAL STATUS AMONG PCOD/PCOS

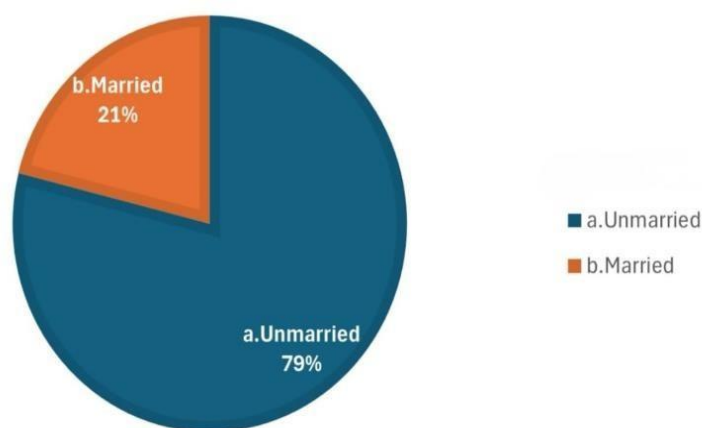


Fig.4.14:Represents themaritalstatusamongwomenwith PCOD/PCOS.

Conclusion: The pie chart shows that the majority of PCOD/PCOS cases are observed among unmarried women compared to married women.

Table4.14:PCOD/PCOSStatusofrelatedpillsconsumption

Consumption	Percentage
Ibuprofen	0%
Meftal-spas	33%
No	67%

PCOD/PCOS STATUS AND RELATED PILLS CONSUMPTION

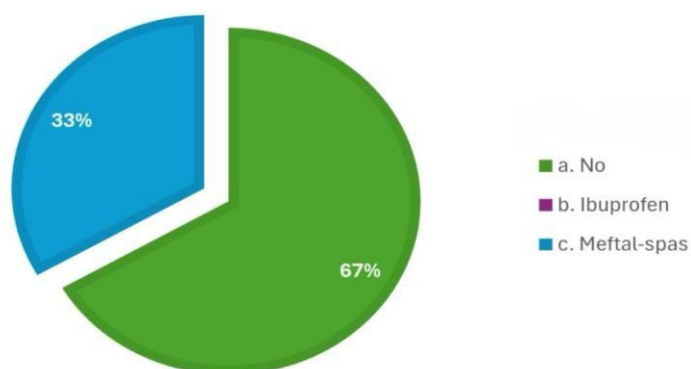


Fig.4.15:ShowstheconsumptionofpillsrelatedtoPCOD/PCOS.

Conclusion: Most of the women's (67%) do not take any pills related to PCOD/PCOS. Only 33% use medications such as Meftal-spas or Ibuprofen.

STATISTICAL ANALYSIS

Chi-Square Test Analysis

➤ Testing the place of residence and occurrence of PCOD/PCOS

H₀: Residence and occurrence are independent **H₁:** Residence and occurrence are dependent

Chi-Square Statistic: 14.1209, P-Value: 0.0069 Degrees of Freedom: 4

Result: Reject null hypothesis and there is dependency between residence and occurrence of PCOD/PCOS

➤ Testing the food consumption and occurrence of PCOD/PCOS

H₀: Food consumption and occurrence are independent **H₁:** Food consumption and occurrence are dependent

Chi-Square Statistic: 2

Result: Reject null hypothesis and there is dependency between consumption and occurrence of PCOD/PCOS

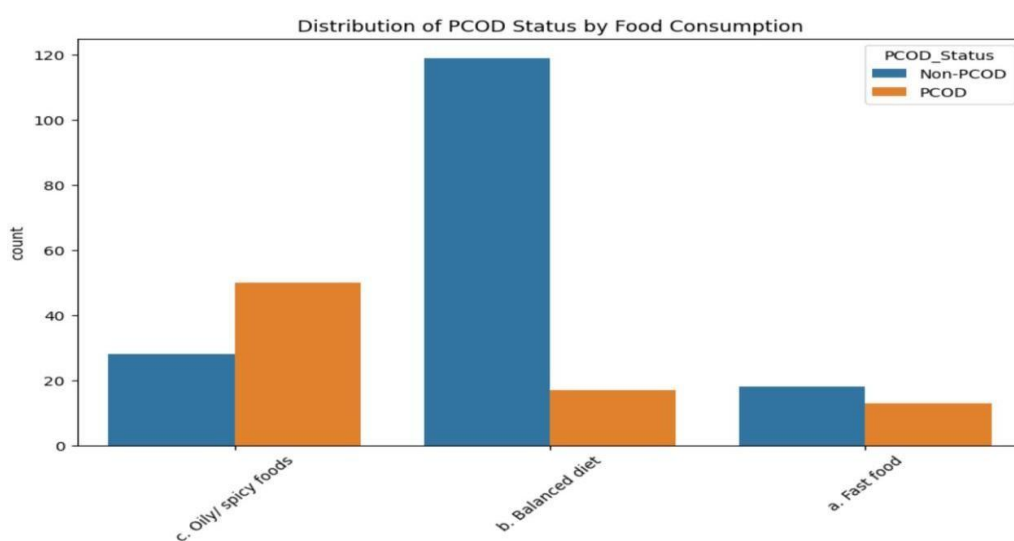


Fig.4.16: Distribution of PCOD by food consumption

Correlation Heatmap

Correlation heatmap are type of plot that visualize the strength of relationship between numerical variables. Correlation plots are used to understand which variables are related to each other and the strength of relationship.

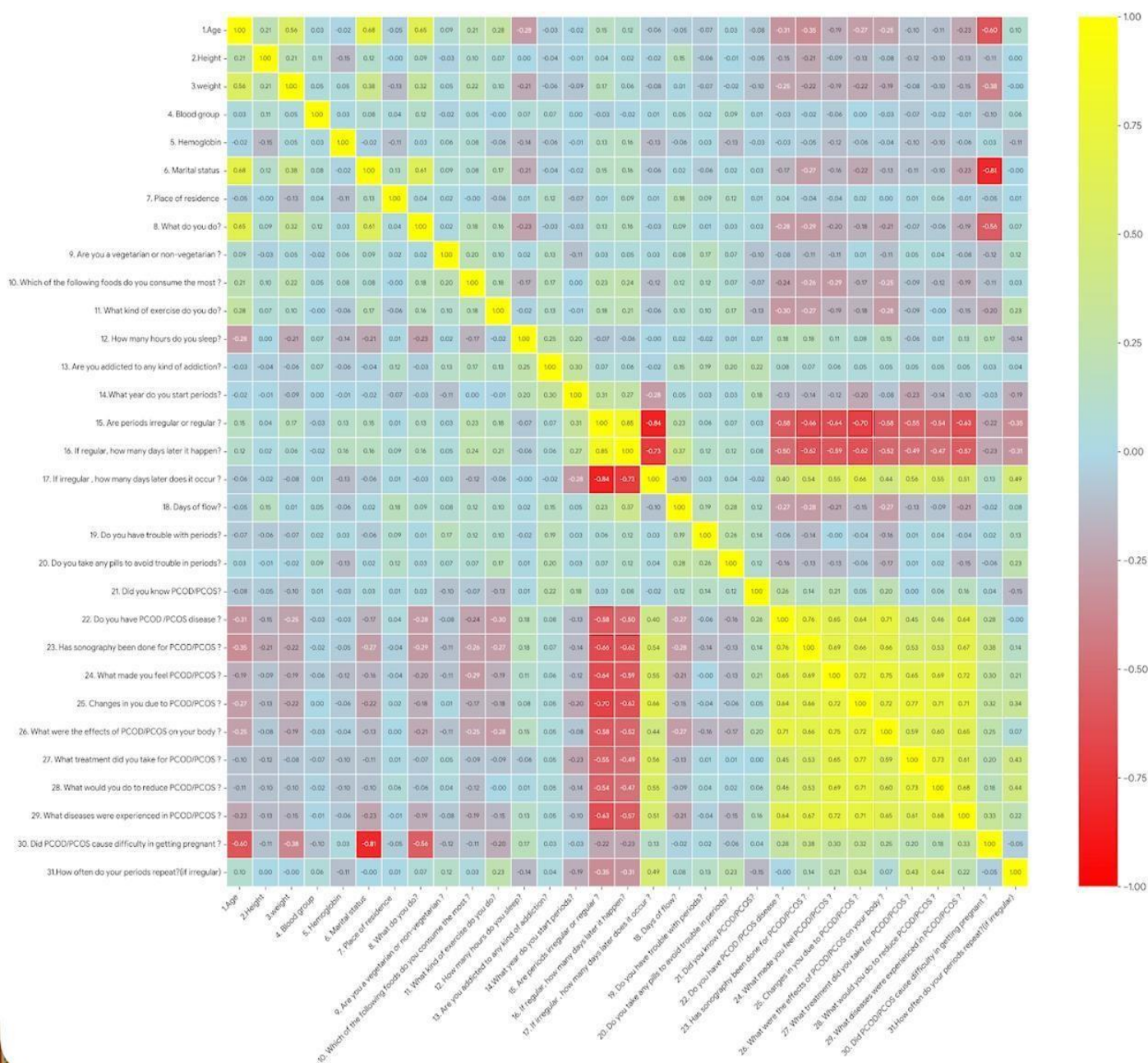


Fig.4.17:Correlationheatmap

Conclusion: Yellow areas show strong positive correlation mainly among PCOD/PCOS and menstrual variables, while red areas Indicates negative relationship. Most other variables appear light Coloured, showing weak correlation.

LogisticRegressionClassifier

Logistic regression is the generalization of linear regression. It is primarily used for predicting binary or multiple class dependent variables because the response variable is discrete, it cannot be modelled directly by linear regression. While logistic regression is a powerful modelling tool, It assumes that the response variable is linear in the coefficients of predictor variable.

Table.4.15:ClassificationReport

Precision	Recall	F1-Score	Accuracy	ROC
0.82	0.82	0.82	0.82	0.94

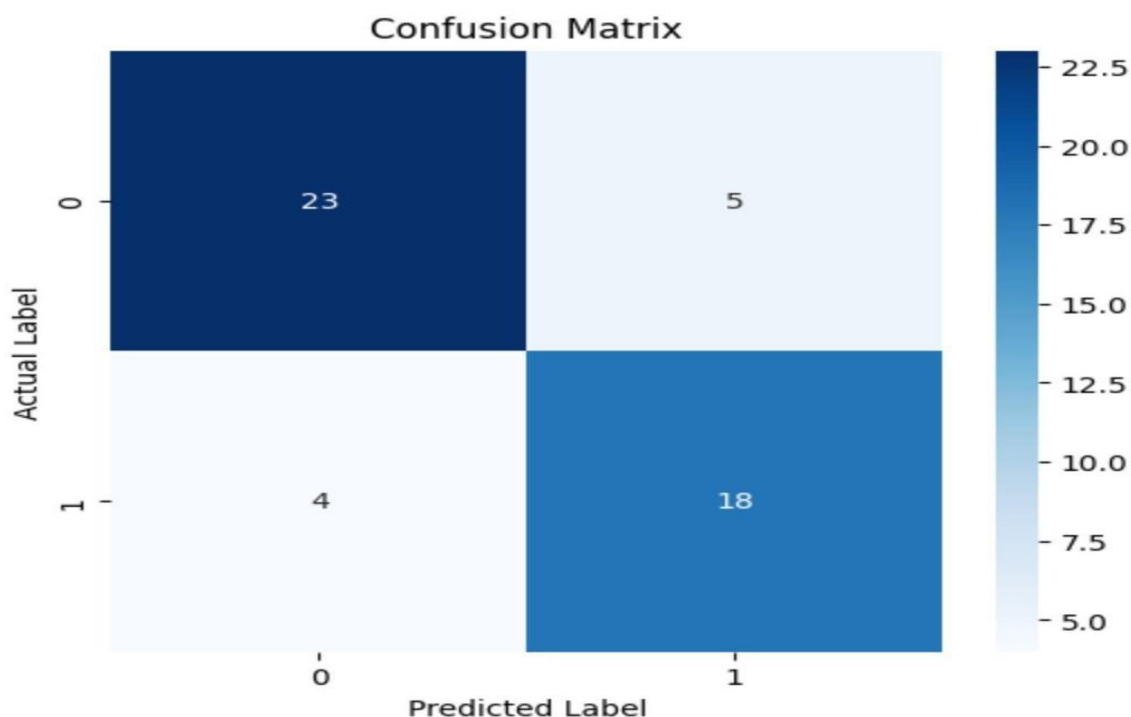


Fig.4.18:Logisticregressionclassifier

Conclusion:82.0%predictedvaluesarecorrectlyclassified

NaiveBayes Classifier

ANaveBayesClassifierisaprobabilisticmachinelearningmodelthat'susedforclassification problem. There are three types of naive bayes classifier, viz.Multinomial naïve bayes, binominalnaive bayesandGaussiannaivebayesclassifier. Inthisproject, weuseMultinomial naïve bayes.

Table4.16:ClassificationReport

Precision	Recall	F1- Score	Accuracy	ROC
0.82	0.82	0.82	0.82	0.95

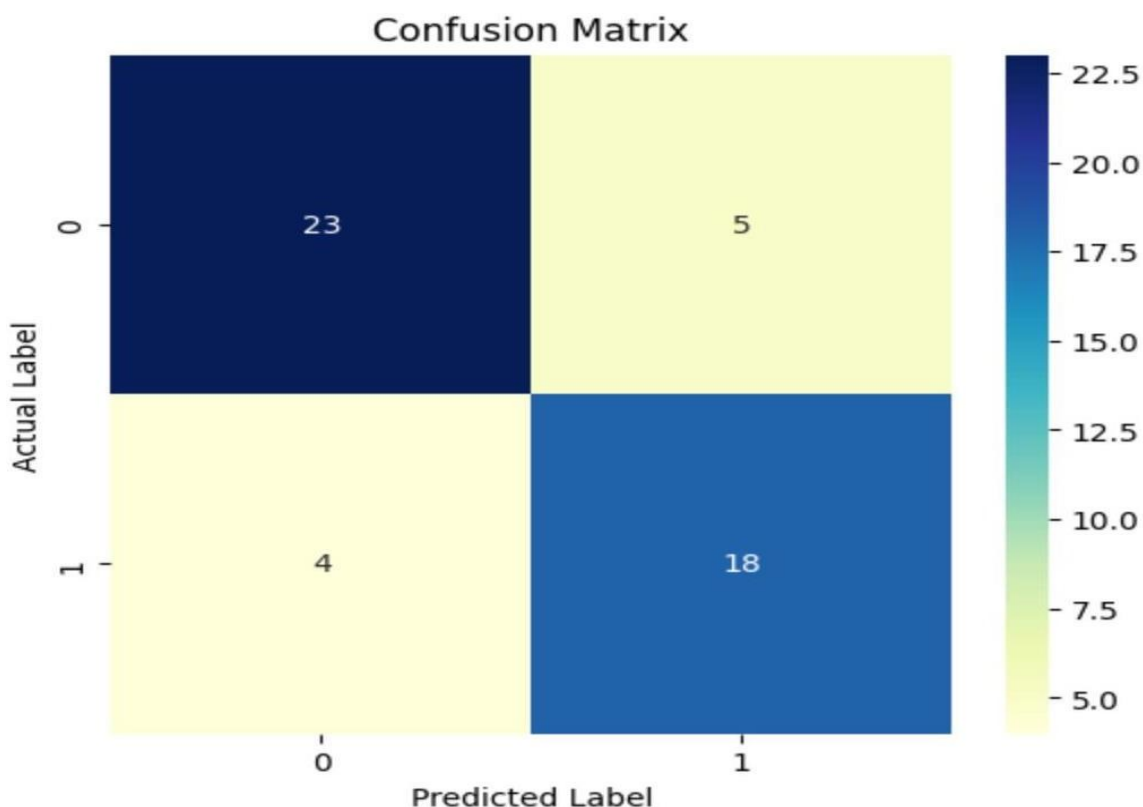


Fig.4.19:Naïvebayesclassifier

Conclusion:82.0%predicatedvaluesarecorrectlyclassified.



Randomforestclassifier

Random Forest is ensemble learning method where it Combine multiple decision tree during training and predict model. Random forest is a classifier that contains a number of decision trees on various subset of the given dataset and takes the advantage to improve the predictive accuracy of that dataset.

Table.4.17:ClassificationReport

Precision	Recall	F1-Score	Accuracy	ROC
0.9	0.9	0.9	0.9	0.95

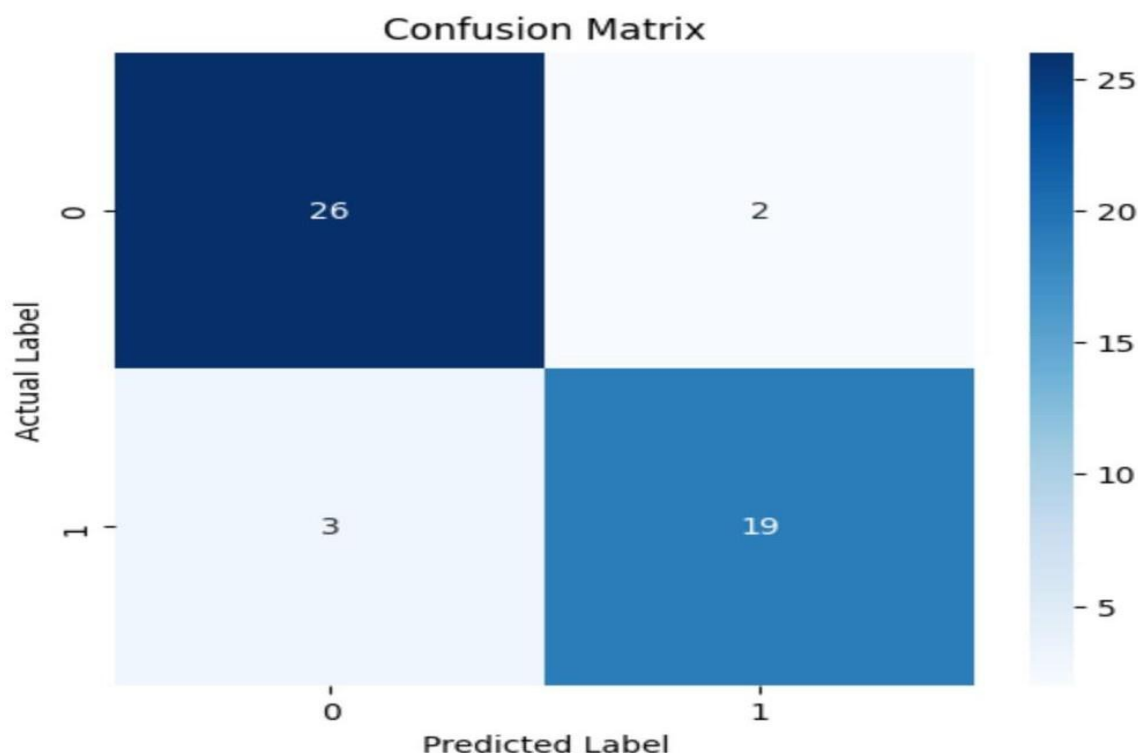


Fig.4.20:Randomforestclassifier

Conclusion:90.0%predicatedvaluesarecorrectly classified.

Support Vector Machine

A Support Vector Machine is a discriminative classifier formally defined by a separating hyperplane. In 2D space this hyperplane is a line dividing a plane in two parts where in each class lay in either side.

Table.4.18:ClassificationReport

Precision	Recall	F1-Score	Accuracy	ROC
0.81	0.78	0.77	0.78	0.93

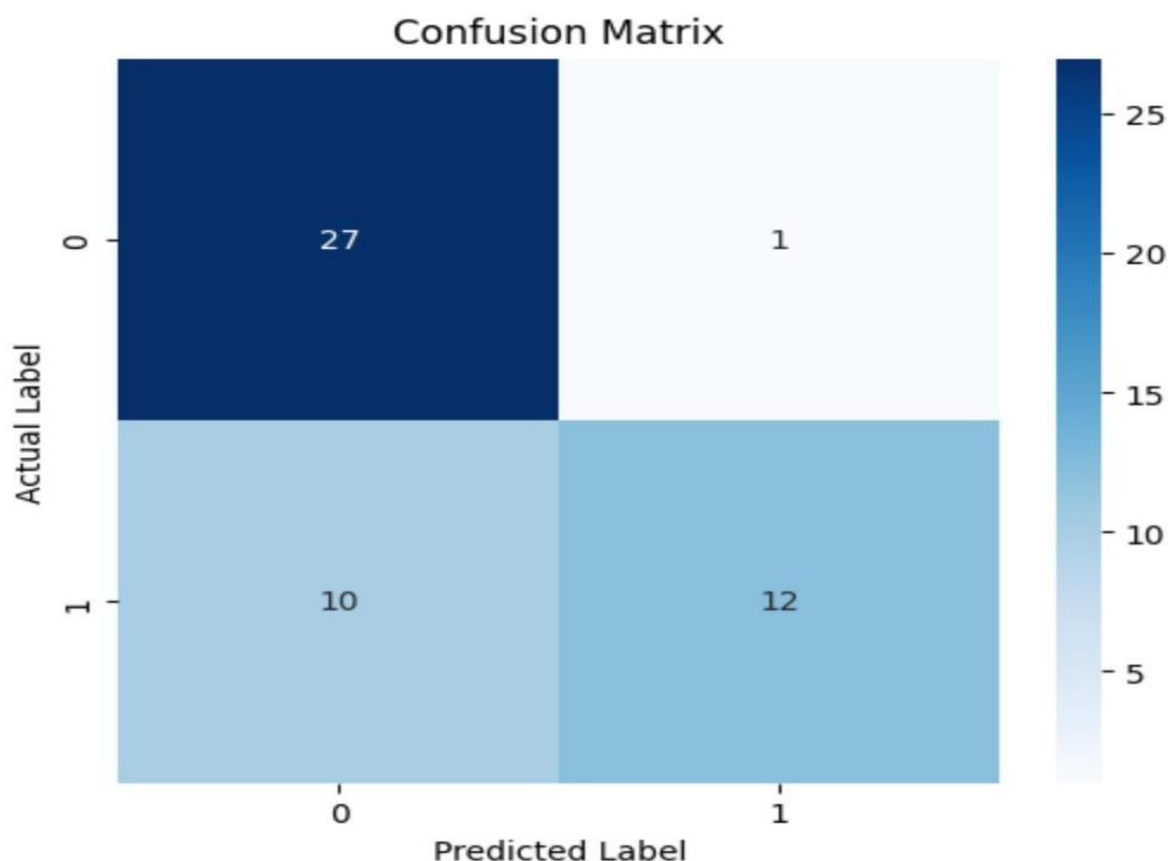


Fig.4.21:Supportvectormachine

Conclusion:78.0%predicatedvaluesarecorrectly classified.

DecisionTreeClassifier

Decision tree algorithm falls under the category of supervised learning. They can be used to solve both regression and classification problems. Decision tree uses the tree representation to solve the problem in which each leaf node corresponds to a class label and attributes are represented on the internal node of the tree. In Decision Tree the major challenge is to identify the attribute further root node in each level. This process is known as attribute selection. We have two popular attribute selection measures:

Table.4.19:ClassificationReport

Precision	Recall	F1-Score	Accuracy	ROC
0.9	0.9	0.9	0.9	0.9

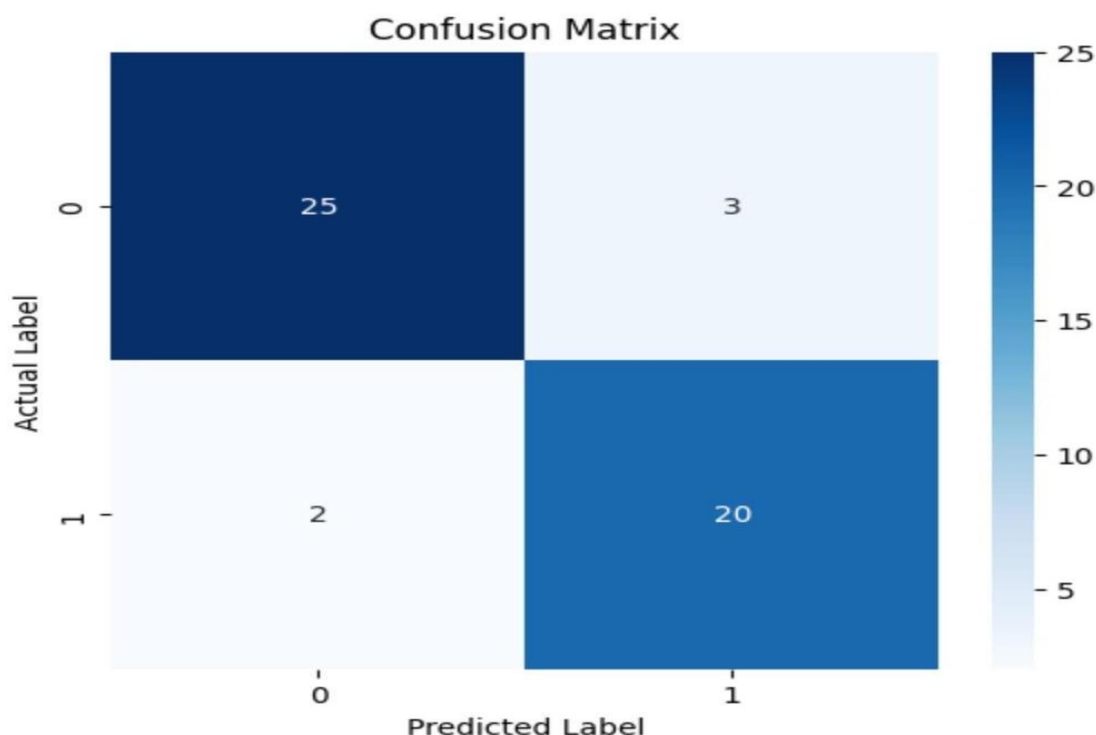


Fig.4.22:Decision tree classifier Conclusion:90.0%predicated values are correctly classified.

K-Nearest Neighbours (KNN) Classifier

The k-nearest neighbours (KNN) algorithm is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve both classification and regression problems. An object is classified by a majority vote of its Neighbours, with the object being assigned to the class most common among its k nearest neighbours.

Table.4.20: Classification Report

Precision	Recall	F1-Score	Accuracy	ROC
0.88	0.88	0.88	0.88	0.91

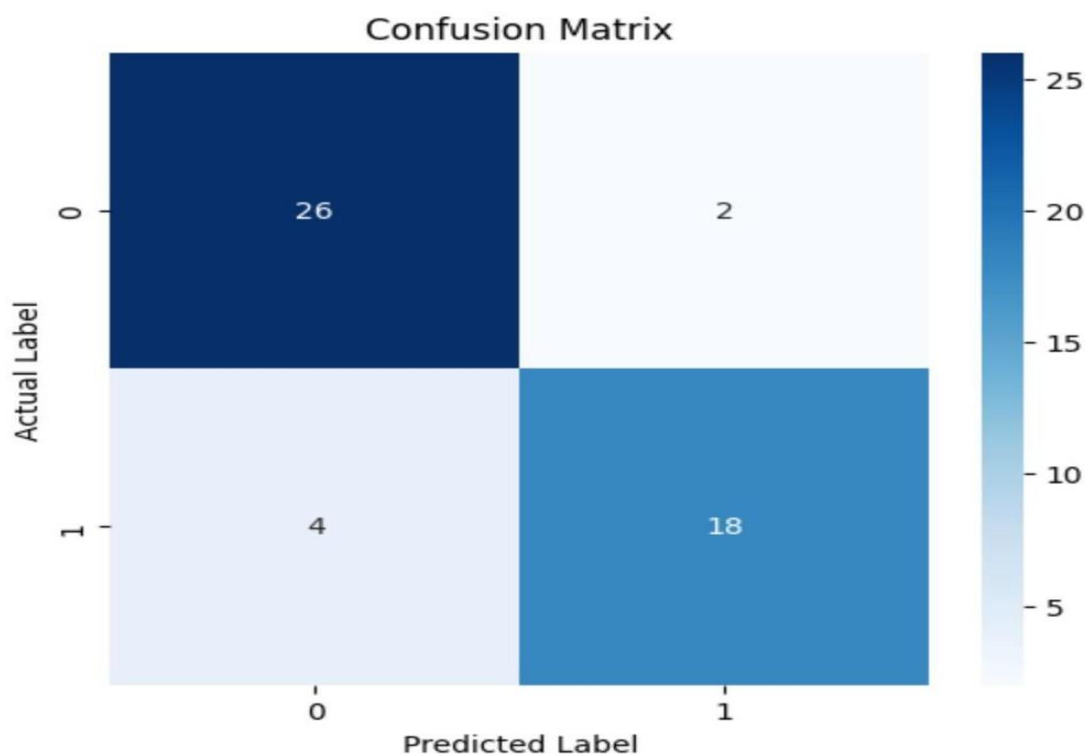


Fig.4.23:K nearestneighboursclassifier

Conclusion:88.0%predicatedvaluesarecorrectlyclassified.

FeatureExtractionbyFactorAnalysis

Itisafeatureextractiontechnique.Thepercentageindicateshathowmucheachevariable contribute to variation in the dataset.

Table.4.21:Futureextractionbyfactorialanalysis

Features	Variationin%
Age	15.14
Height	9.14
Weight	4.41
Bloodgroup	4.26
Hemoglobin	3.83
Maritalstatus	3.16
Placeofresidence	3.04
Whatdoyoudo?	2.63
Areyouavegetarianornon-vegetarian?	2.56
Whichofthefollowingfoodsdoyouconsumethe most?	2.48
Whatkindofexercisedoyoudo?	2.27

Howmanyhoursdo yousleep?	2.22
Whatyeardoyoustartperiods?	2.13
Areperiods irregularor regular?	2.10
Ifregular,howmanydays laterithappen?	1.96

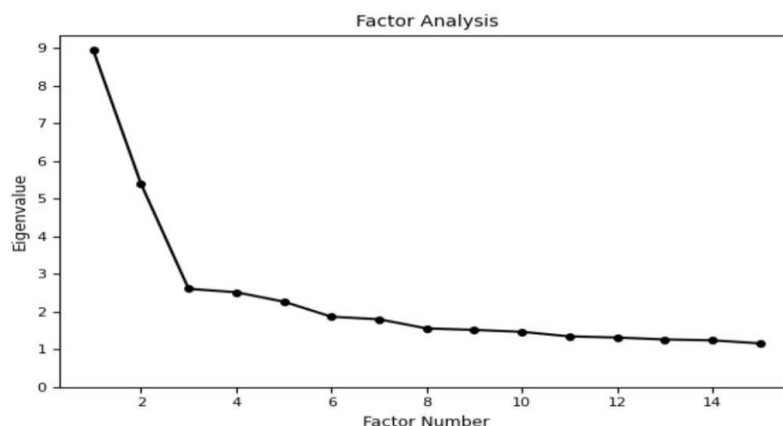


Fig.4.24:Featureextractionbyfactorialanalysis

Conclusion:Weextracted13componentsfrom31componentswhichcoversmaximum variation (61%) within dataset.

ClassificationResults

To classify women's with PCOD/PCOS from given variables, we applied following techniques.

Table.4.22: Classification results

Performance			
Classifier	Accuracy	Recall	F-1score
Randomforest	0.77	0.77	0.72
KNN	0.71	0.71	0.66
LogisticRegression	0.67	0.67	0.68
Decisiontree	0.71	0.71	0.71
NaiveBayes	0.04	0.04	0.03
SVM	0.73	0.73	0.67

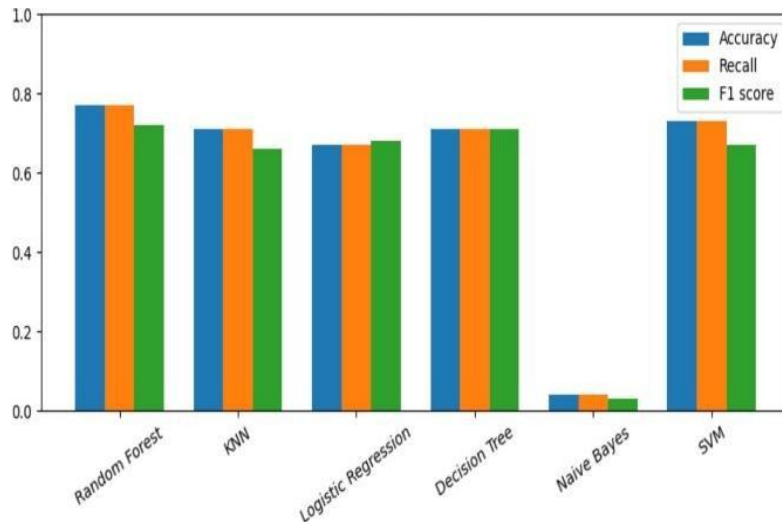


Fig.4.25:Classificationresults

Conclusion: From above, we can conclude that Random Forest model gives highest (77%)accuracy of classification.

ReceiverOperatingCharacteristic(ROC)

ROCcurveiscommonlyusedtovisualizetheperformanceofthe classifier.

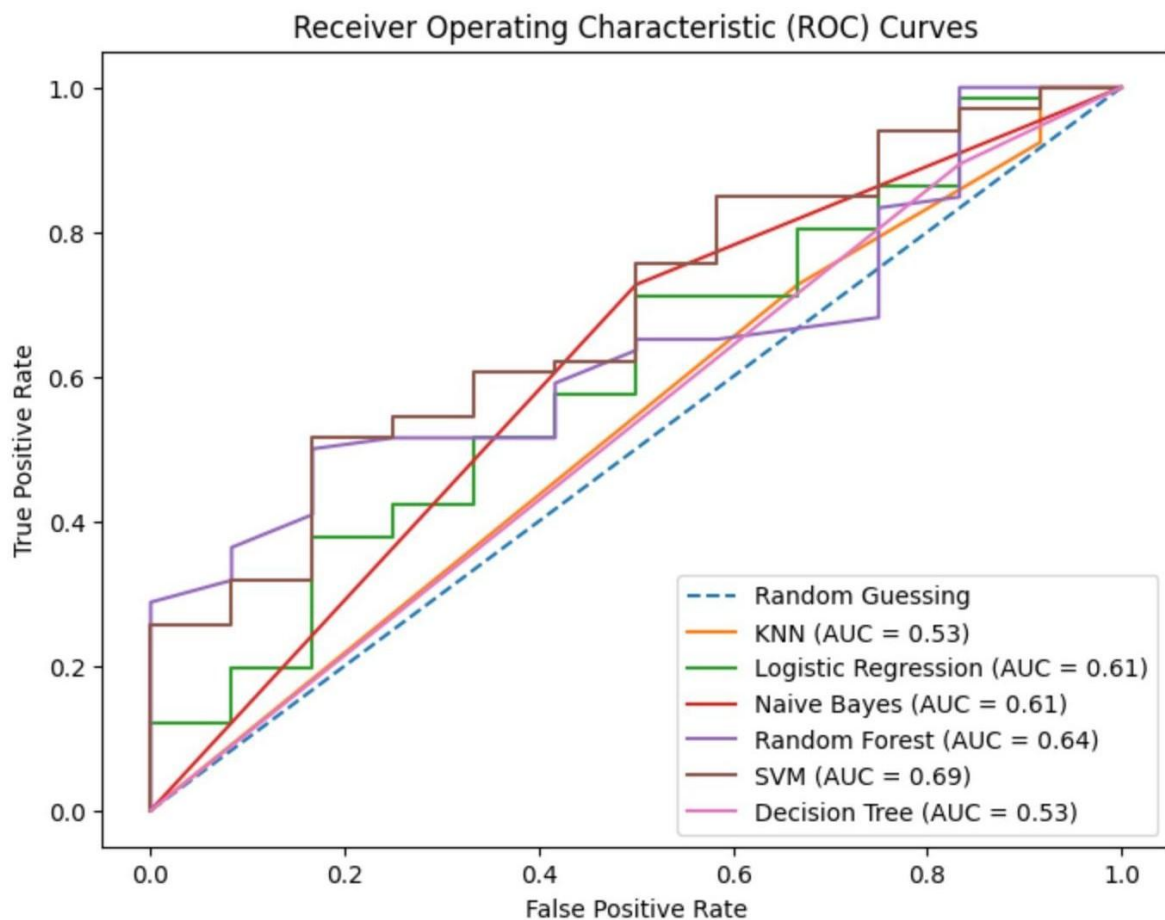


Fig.4.26:Receiveroperating characteristic

Conclusion: From the above ROC curve, the best model is SVW with AUC=0.69.

Suggestion to control PCOD/PCOS



Fig.5.1: Suggestion to control PCOD/PCOS

Classification Techniques

➤ KNN

```
from sklearn.neighbors import KNeighborsClassifier
k=KNeighborsClassifier(n_neighbors=5)
k.fit(X_train_res,y_train_res)
pred=k.predict(X_test)
pred accuracy
metrics.accuracy_score(y_test,pred)
print("Accuracy from KNN="accuracy)
print(classification_report(y_test,pred))
print(confusion_matrix(y_test,pred))
```

➤ Naïve Bayes

```
from sklearn.naive_bayes import GaussianNB
n=GaussianNB()
n.fit(X_train_res,y_train_res)
class_pred=n.predict(X_test)
class_pred accuracy
metrics.accuracy_score(y_test,class_pred)
print("Accuracy from Naïve Bayes accuracy")
print(classification_report(y_test,class_pred))
print(confusion_matrix(y_test,class_pred))
```

➤ **LogisticsRegression**

```
fromsklearn.linearmodelimportLogisticRegressionlogistic=LogisticRegression() logistic
fit(X_train_res,y_train_res) pred3=logistic.predict(X_test)pred3
accuracy2=metrics.accuracy_score(y_test,pred3)print("AccuracyoflogisticsRegression=", accuracy2)
print(classification_report(y_test,pred3))print(confusion_matrix(y_test,pred3))
```

➤ **RandomForest**

```
fromsklearn.ensemble
importRandomForestClassifierRandomForestClassifier(r_estimators=10)r.fit(X_train_res,y_train_res) pred5=
r.predict(X_test)pred5
accuracy5=metrics.accuracy_score(y_test,pred5)print("AccuracyofRandomForest" accuracy5)
print(classification_report(y_test,pred5)) print(confusion_matrix(y
test,pred5))pred5r.predict(X_test)pred5accuracy5=metrics.accuracy_score(y_test,pred5) print("Accuracy of
Random Forest", accuracy5)
print(classification_report(y_test,pred5))print(confusion_matrix(y_test,pred5))
```

➤ **DecisionTree**

```
fromsklearn.tree
import Decision TreeClassifierD=Decision Tree Classifier(max_depth=5) D=D.fit(X_train_res,y_train_res)
pred4=D.predict(X_test) pred4 accuracy4
metrics.accuracy_score(y_test,pred4)print("AccuracyofDecisionTree",accuracy4)
print(classification_report(y_test,pred4)) print(confusion_matrix(y_test,pred4)) from sklearn
import treeT=tree.export_text(D) print(T)
fig=plt.figure(figsize=(25,18))T1=tree.plot_tree(D)
```

➤ **SupportVectorMachine**

```
fromsklearn.svm
importSVCsvmSVC(svm.fit(X_train_res,y_train_res)pred6=svm.predict(X_test)pred6
print(confusion_matrix(y_test,pred6))a6=metrics.accuracy_score(y_test,pred6) print("Accuracy from
Support Vector Machine", a6)
print(classification_report(y_test,pred6))
```

➤ **ReceiverOperatingCharacteristic(ROC)Curves**

```
importnumpyasnp
import matplotlib.pyplotaspit
from sklearn.datasets import make_classification from sklearn.model_selection import train_test split
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, auc
```

➤ Standardize the features

```
Scaler=StandardScaler()
X_train=Scaler.fit_transform(X_train) X_test = Scaler.transform(X_test)
```

➤ Initialize all classifiers

```
Classifiers={
    "KNN":KNeighborsClassifier(),
    "LogisticRegression":LogisticRegression(), "Naïve Bayes": GaussianNB(),
    "RandomForest":RandomForestClassifier(), "SVM": SVC(probability =True),
    "DecisionTree":DecisionTreeClassifier()
```

SUMMARY AND CONCLUSION

➤ Summary:

Polycystic Ovary Syndrome (PCOS) or Polycystic Ovary Disease (PCOD) is one of the most common hormonal disorders affecting women of reproductive age. The present study was conducted to analyze the prevalence and health impact of PCOD/PCOS among women in the selected population.

In this study, a total of 260 women aged between 12–45 years were included, among which 83 women were diagnosed with PCOD/PCOS. Data were collected using questionnaires, physical examination parameters such as BMI, blood pressure, and clinical symptoms, along with lifestyle and dietary habits. The study was conducted in colleges, nearby villages, and gynecology hospitals.

The results showed that PCOD/PCOS was more common in younger women, especially in the 20–25 years age group. Menstrual irregularities were frequently observed among affected women. Lifestyle factors such as stress, hormonal imbalance, unhealthy diet, and lack of physical activity were identified as major contributors to the occurrence of the disorder.

The analysis also showed that many women experienced symptoms such as stomach pain, back pain, irregular menstrual cycles, and pregnancy difficulties. Around 73% of women reported pregnancy-related problems associated with PCOD/PCOS. Urban women showed a higher prevalence compared to rural

women.

Different machine learning classification techniques such as Logistic Regression, Naïve Bayes, Random Forest, Support Vector Machine, Decision Tree, and K-Nearest Neighbors were applied to analyze the dataset. Among these methods, the Random Forest model provided the highest accuracy for classification, indicating its effectiveness in predicting PCOD/PCOS cases.

The study highlights that early diagnosis, awareness, and lifestyle modification play a crucial role in reducing the complications associated with PCOD/PCOS.

➤ Conclusion:

From the present study, it can be concluded that PCOD/PCOS is a significant health problem among women of reproductive age. The prevalence of the disorder is increasing, especially among young women due to lifestyle changes, stress, and dietary habits.

The findings indicate that menstrual irregularities, hormonal imbalance, obesity, and stress are major risk factors associated with PCOD/PCOS. The condition not only affects reproductive health but also leads to metabolic disorders, psychological issues, and pregnancy complications.

Statistical and machine learning analysis revealed that Random Forest and Decision Tree models showed better prediction accuracy compared to other classification methods.

Therefore, early screening, proper medical treatment, regular exercise, healthy diet, and lifestyle management are essential to control and prevent the complications of PCOD/PCOS. Increasing public awareness and health education programs can help women identify symptoms early and seek appropriate medical care.

Overall, this study emphasizes the importance of timely diagnosis and preventive healthcare strategies to reduce the burden of PCOD/PCOS and improve women's reproductive and overall health.

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