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A IoT-Based Predictive System for Real-Time PCOS Risk Assessment

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***Abstract* – This Research Paper discusses the advancement of an intelligent and non-invasive framework for the early prediction of Polycystic Ovary Syndrome (PCOS) by using the integration of the Internet of Thing (IoT) and machine learning concepts. The proposed system uses the IoT concept by employing an embedded system based on the ESP32 module to obtain real-time physiological parameters such as the body temperature and heart rate of the patient, as well as other relevant parameters from the connected sensors. The collected parameters are then sent to the cloud environment to pre-process the data and make the predictions using the supervised learning concept. The system architecture includes three major components: the data acquisition module, the predictive analytics module, and the user interface module. The Predictive analytics module uses classification algorithms to train the predictive model and obtain accurate results in the early-stage detection of the disease. The experiment results indicate the effectiveness of the system in terms of the reduced reliance on conventional diagnostic techniques. This system is proposed as a way to provide timely information that can be used to improve the healthcare condition of women suffering from PCOS.**

Keywords - PCOS, Internet of Things (IoT), Machine Learning, ESP32, Health Monitoring, Predictive Analytics, Embedded Systems.

1. INTRODUCTION-

1.1 Challenges in Early Prediction of PCOS

Polycystic Ovary Syndrome (PCOS) is a common disorder that occurs in women of reproductive age. PCOS prevents the production of eggs since it causes serious complications during pregnancy among females suffering

from PCOS.[1] Some of the symptoms that are commonly

associated with PCOS include high levels of androgens (male hormones), irregularities of menstrual periods, polycystic ovaries, and metabolic disorders. Despite the high prevalence of endocrine disorder, early diagnosis is a major problem because of the diversity of the demonstration of the disorder, including hormonal imbalance, irregular menstrual cycle, weight changes and metabolic disorders. Women with PCOS undergo infertility, resulting in gynaecological cancer. [3] The traditional method is expensive, Time-consuming and not easily available in remote ares.

Generally, The treatment for PCOS [4] is through lifestyle changes, weight loss, and proper nutrition. Women who suffer from PCOS are more likely to develop anxiety disorders and are highly vulnerable to

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depression [5]–[6].the unawareness, absence of health monitoring and the delay in consulting doctors cause the delay in the diagnosis of the disorder which may lead to serious health complications, including infertility, diabetes, and heart related problems in future. A new study suggests that PCOS affects 4.8% of white American women, 8% of black American women, 6.8% of Spanish women, and 31.3% of Asian women. [7]. In addition, the current health care system is not proactive which makes the need for an intelligent system that can predict the disorder at early stages of manifestation of a necessity.

1.2 *Proposed PCOS Prediction System Overview*

In order to overcome these challenges, this paper suggest an integrated IoT-based PCOS Prediction System, which in-corporates the concept of machine learning based prediction using physiological data acquisition. The system will utilize an embedded system based on ESP32 technology, which will acquire vital health parameters, including body temperature, heart rate and other relevant parameters, using connected sensors.

The acquired parameters will be sent to a cloud or processing unit which will be used to preprocess and analyse the parameters using machine learning algorithms. In [8], Various models were compared, namely CNN, ANN, SVM, DT, and KNN, and feature selection techniques were implemented to predict the PCOS status. Among all the algorithms, the best-performing algorithm was obtained using RF. In [9], SVM, LR, NB, and KNN techniques were implemented to check whether a woman is suffering from PCOS or not. The feature selection was done using chi-square technique to get top 30 features.The system will be able to identify patterns and provide prediction results for PCOS. However, a user interface will be incorporated, which will provide health-related information to users and allow them to take preventive measures. Examining such an alternative means of diagnosing could help enable the process of early detection and thereby help prevent any potential health complications. [10]

This system will provide a solution to the gap between conventional diagnostic techniques and smart healthcare systems.

1.3 *Research Contributions*

This paper aims to propose a novel approach for the early prediction of Polycystic Ovary Syndrome (PCOS) by employing real-time monitoring based on Internet of Things (IoT) technology and machine learning analytics. The proposed framework uses embedded platforms based on ESP32 to collect continuous physiological data from connected sensors. This approach collects important health parameters related to PCOS. The data is then processed to identify patterns for early-stage PCOS using supervised machine learning algorithms (SML).

This solution utilizes an integrated approach that includes the combination of embedded hardware along with cloud-based data analytics to offer a robust and effective solution for the goal of health monitoring. Further, this solution includes a user-friendly interface as well, so that users can view their health parameters, thus promoting proactive healthcare management. In addition, the framework is based on a cost-effective approach, allowing for easy implementation in environments where PCOS diagnostic facilities may not be readily available. Thus, the proposed framework for continuous physiological monitoring, machine learning analytics and a user- friendly interface provides a comprehensive solution for non-invasive prediction of early-stage PCOS, thereby overcoming the existing limitations of conventional PCOS diagnostic techniques.

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2. Literature Review

Ref. No.	Title of the Paper	Author (s)	Year	Publication Source	Methodology	Conclusion
1	*AI-Powered Hybrid Diagnostic System for Polycystic Ovary Syndrome Using Clinical and Ultrasound Features*	Patel R., Desai N	2025	IEEE Access	Hybrid Machine Learning model combining clinical and ultrasound data	Achieved improved diagnostic accuracy but lacks IoT integration and real-time data usage
2	*A Hybrid Deep Learning System for Polycystic Ovary Syndrome Prediction*	Kavitha K., Aarthi M	2024	IEEE Xplore	Deep Learning model trained on hospital EMR datasets	Effective prediction but limited to static data; no real-time IoT deployment
3	*AI and IoT Integration for Early Detection of Women's Reproductive Disorders*	Rao P., Joshi S	2024	IEEE Sensors Journal	IoT-based health monitoring system integrated with AI	Useful for general health monitoring but not specifically focused on PCOS prediction
4	*A Review and Meta-Analysis on PCOS: Its Prevalence and Effect on Health Impact of PCOS*	Coffin T.	2023	Elsevie r Journal of Reprod uctive Health	Statistical analysis and meta-analysis of PCOS data	Provides insights into prevalence but lacks technical or predictive system implementation
5	*A Systematic Review and Research Agenda for*	Suha S.A.	2023	Springe rLink	Systematic review of ML-based PCOS identification techniques	Emphasized need for real-time ML- based automated PCOS detection systems

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	Computer-Assisted PCOS Identification					
6	*Polycystic Ovary Syndrome: An Updated Overview*	Yasmin A.	2022	Wiley Online Library	Clinical study and review of diagnostic criteria	Focuses on medical diagnosis; lacks computational or AI-based solutions
7	*IoT-Based Health Monitoring System for Women with PCOS*	Meenakshi Sharma, Ritu Pahwa	2022	IEEE International Conference on IoT Applications	IoT-based hardware system for monitoring health parameters	Effective monitoring system but does not include ML- based prediction
8	*Predicting PCOS Application of Machine Learning Algorithms and Feature Selection Techniques*	Laxmi Kumari, Sanjay Agrawal	2021	IJIRCSE	Machine learning algorithms along with feature selection techniques	Accurate prediction but lacks real-time data and IoT integration
9	*Machine Learning Approaches for Reproductive Health Prediction*	Gupta R., Singh P.	2020	IEEE International Conference Computational Intelligence	General ML models for reproductive health prediction	Broad prediction approach; not specifically focused on PCOS

Table No.1: Literature review table

Patel R., Desai N. in 2025 developed a promising AI Powered system to diagnose Polycystic Overy Syndrome. In their research they developed a hybrid machine learning model that used both clinical and ultrasound imaging features to improve diagnostic accuracy. Because of this their model perform better compared to traditional single source diagnostic method. The system purely does software-based analysis meaning it works on data that has been already collected rather than monitoring patient in real time.

Kavitha K., Aarthi M. in 2024 they developed a hybrid deep learning framework for easier diagnosis of PCOS using electronic medical records obtained from hospitals. There model involved training deep learning model such as Artificial Neural Network on structured hospital dataset with preprocessing steps including feature

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selection and normalization to get more accurate prediction. The model gains reliable performance in detecting Polycystic Overy Syndrome patterns.

Rao P., Joshi S. in 2024 presented an AI-IoT based system for early detection of women's reproductive disorders. Their system included the use of IoT sensors to collect the physiological data which were transmitted to cloud platform were AI-model analyse the data for anomalies. It was a real-time patient monitoring system however it did not specifically target Polycystic Overy Syndrome prediction.

3. METHODOLOGY

3.1 *Dataset Description*

Our study worked with a medically validated PCOS dataset collected from hospitals and diagnostic centre's across India. The original data was compiled by Kottarathil and colleagues and includes health records from 541 women of reproductive age who were screened for PCOS—

Suha S.A. in 2023 presented a systematic review on ML assisted Polycystic Overy Syndrome identification. The methodology involved reviewing and analysing existing machine learning and data driven approaches for Polycystic Overy Syndrome detection comparing their performance, limitations and applicability. The study highlighted the effectiveness of ML techniques while identifying the gaps, automation and real-time processing.

There were 185 women that were affected by the disease liken to 356 who did not have the disease.The data is made up of a combination of quantitative variables and qualitative variables for each woman's medical records. Each of the patients was bound's the age bracket of 18 to 45 years:

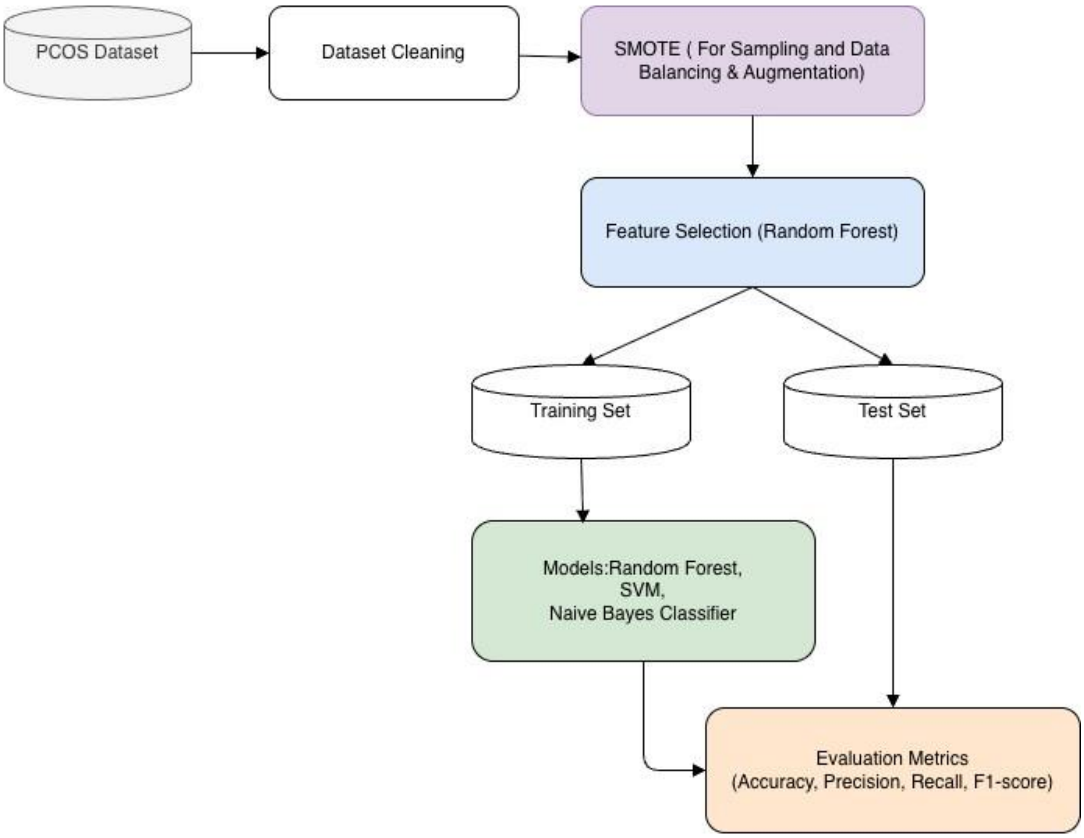

Fig 1. PCOS Prediction System through Machine Learning Pipeline

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basic demographics like age, height, weight, heart rate and BMI; lifestyle and physical indicators like menstrual cycle length, marital status, acne, excessive hair growth, and skin darkening; as well as reproductive history including pregnancy status.

The reason this dataset could be considered valuable is because it defines PCOS risk in terms of three classes - High, Medium, and Low. Thus, it gives a much clearer picture of PCOS as a spectrum disease. Yet, it was observed that there was some degree of class inequaility in the data, where in there were more non-PCOS patients than PCOS patients.

3.1.1 Balancing the Dataset with SMOTE

This was done in order to address this problem and make ensure that our model learns more efficiently. Like this, we were able to increase our sample size from 541 to around 3,000 through a technique known as SMOTE (Synthetic Minority Oversampling Technique). SMOTE is an intelligent means of generating synthetic patient records in contrast of duplicating the data.

Management of missing data: There are a number of statistical methods used for management of missing data depending on how much data is missing and its importance as a variable [14]. The SMOTE algorithm uses an instance of PCOS from the database we already have and analyzes other instances of it. Instead of replicating the same instance, it creates new instances based on the similarities it finds in those cases; the difference is, these are not exact copies of those instances but are in fact combinations of all those similar instances [11]. This decreases bias towards the maximum class.

Using the SMOTE technique on just the PCOS patients created the data set more even, allowing the model to be equally effective in recognizing both types of samples. This approach helped to avoid a model which would only predict “not PCOS” because it was the dominant class. The outcome is an enhanced model for PCOS prediction with higher accuracy and effectiveness.

3.2 *Correlation Analysis*

3.2.1 Understanding the Data: What Correlates with PCOS?

In order to survey connections between various health indicators, along with between them and PCOS, a correlation matrix was constructed by employing Pearson's coefficient. In easy terms, what it aims at is revealing whether two features tend to change their values simultaneously – when one,will the other one also rise (fall)? Understanding relations between features is an extremely important step before creating any sort of predictive model.

3.2.2 PCOS Indicators

Symptoms of PCOS: Symptoms of PCOS are explained by Johns Hopkins Medicine, which include the being away of menstrual periods, infrequent or very light periods, excess body hair growth, weight gain, acne, hair loss, difficulty getting pregnant, and dark patches on the skin of the back of the neck, groin, and breasts areas. [15]. Some fascinating observations could be drawn from the correlation heatmap we produced. Certain clinical symptoms have exhibited moderate to highly correlated values with PCOS. These features included skin hyperpigmentation (0.65), excess hair growth (0.55), and weight gain (0.50), with high correlation values. Other highly correlated features were irregular menstrual periods (0.48) and high fast food consumption (0.47). Selecting a relevant set of features is obtained via FS.

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Skin Darkening(Y/N)	0.475733
Hair growth(Y/N)	0.464667
Weight gain(Y/N)	0.441047
Cycle(R/I)	0.401644
Fast food (Y/N)	0.376183
Pimples (Y/N)	0.286077
Weight(kg)	0.211938
BMI	0.199697
Hair loss (Y/N)	0.172879
Waist(inch)	0.164598
Hip(inch)	0.162297

Table no.2: Full Feature correlation with target

3.2.3 Physical Measurements

Strangely enough, the physical parameters including Body Mass Index, weight, and hip circumference were got to be minimum strongly associated with PCOS with correlation coefficient values of 0.25 and 0.27. Therefore, the real kicker comes after. The physical parameters are highly correlated between themselves. The correlation between Body Mass Index and weight is extremely high at 0.93. Logically enough, this is true because Body Mass Index is calculated based on the data about weight. Also, there is a strong connection between weight and hip circumference (0.71) and Body Mass Index and hip circumference (0.68).

3.2.4 What This Means for Our Model

What is the key point? Symptom characteristics such as skin, hair, and menstrual abnormalities have Maximum predictive power for PCOS compared to just using physical parameters. The optimal set of parameters can be chosen through feature selection (FS), where irrelevant parameters are ignored to improve accuracy of learning [12,13]. With this knowledge, we were able to use feature selection to develop a model that was simple to understand or recognized. By focusing on the features that truly matter, we created a smarter, more efficient prediction system.

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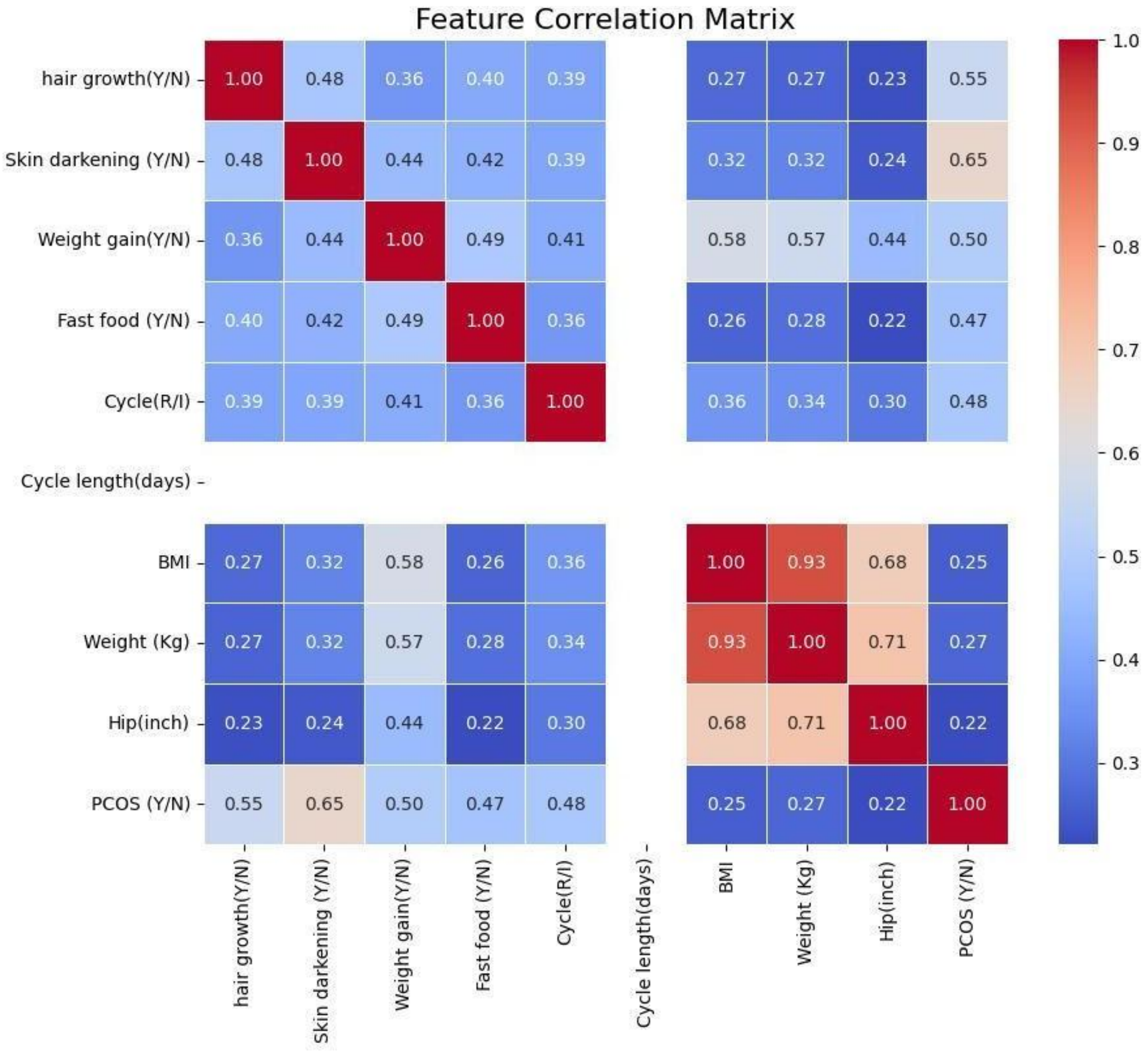

Fig2: Heatmap showing corelaion between features and PCOS

3.3 *Predictive Analytics and Machine Learning Model*

The suggested system utilizes a Random Forest classifier as a tool in the prediction of PCOS based on anthropometric and physiological parameters. The Random Forest classifier is chosen based on its strength and effectiveness in handling non-linear relationships and reducing the problem of over- fitting in the prediction process. The prediction model based on set of parameters such as weight, body mass index (BMI), waist hip ratio, and other relevant health parameters related to PCOS. In comparison to the traditional prediction methodology, which is based on offline data sets, the suggested methodology is effective in acquiring real-time data from sensors, which is then fed into the trained model for prediction purposes. The algorithm is based on the generation of multiple decision trees and the prediction of the majority voting mechnism of the decision trees.

The prediction process is based on a structured evaluation mechanism, in which the parameters are evaluated together to arrive at a comprehensive risk score related to PCOS. The suggested methodology is effective in handling the complexities of the parameters and reducing the chances of false predictions. The final prediction is then reflected on the user interface, which provides a clear indication of the risk levels and the need for further consultation in the case of PCOS diagnosis.

4. *System Architecture*

AIoT-Based Predictive System is a medical application that includes physical hardware data, Machine Learning diagnosis, and medical management. The application provides a pipeline for patients to track their health, and the data is used by a Machine Learning engine to help doctors make a final diagnosis.

4.1 *Backend Infrastructure*

4.1.1 Core technologies and Dependencies

The backend of the proposed system is designed using a scalable architecture for real time data acquisition, processing and machine learning inference. The proposed system is using Node.js and express as a primary server for request handling and communication management.

4.1.2 Data pre-processing and integration sub-system

The backend features the structured pipeline for data integration. It uses Handshake Protocol for mapping of sensor data to correct user session for preventing data mismatch when system is used by multiple users. It performs functions like Data Aggregation, Database Storage, Queue-Based processing.

4.1.3 Machine Learning Pipeline

The machine learning system as a micro services use the FastAPI service network and perform

5. *PCOS prediction Algorithm and pipeline processing*

The proposed approach estimates the likelihood chances for PCOS using a machine learning approach. Pipeline supported by structured data processing. It brings together information provided by users, real-time readings from sensors, and a Random Forest classifier to generate accurate predictions.

5.1 *Data Processing*

The raw data collected from sensors and user inputs function like feature processing, model inference response handling and asynchronous execution.

4.2 Frontend Architecture

The frontend has been designed and implemented as a single page application using React.js which provides interractive user interface for patient dashboard, doctor and admin interface.

4.2.1 User Interaction Workflow

Data Entry Interface: users are prompted to enter various symptoms such as cycle length, cycle type(R/I), skin darkening, hair growth, pimples, hair loss, weight gain, fastfood consumption through structure interfaces.

Session Linking: A unique handshake code is generated and utilised for hardware data and session.

Result and Visualisation: Healthcare professional can access and utilise the data and result prediction for providing prescriptions and recommendation.

4.2.3 Technology Stack

React.js: it has been used for creating a dynamic and interactive interface in real-time interaction.

TailWind CSS: it is used to create consistent and efficient interface.

Authentication: it is used for providing secure authentication and maintaining sessions differences in scale. Various methods of statistical analysis can be used to handle missing data problems depending on the extent of data loss and the significance of the missing feature.[17] If the proportion of missing data is within 5% to 10%, classical statistical methods such as the mean, max, and mode method are highly effective. When the fraction of missing values is 20–50%, sophisticated approaches, such as hot-deck [18]. To address this, preprocessing is performed before feeding the data into the prediction model. Sensor readings - such as temperature, weight, and pulse rate - are first checked to remove noise and detect may contain inconsistencies, missing values, or

any irregularities. At the same time, user-supplied details, including lifestyle habits and menstrual cycle information, are reevaluated to ensure completeness. Finally, the combined dataset is

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normalized so that all features are on a consistent scale, which helps enhance the overall performance of the machine learning model.

5.2 *Algorithm*

The primary method used for predicting includes the Random Forest Classifier, which is a type of ensemble learning technique, where many decision trees are produced during training. These decision trees use the mentioned input data, and come up with their own predictions. The randomness involved in generating the decision trees is ensured through the inclusion of randomness in the algorithm, minimizing variance and overfitting.[16] eventually, the majority rules. It is evident that by involving many decision trees in the voting, the prediction becomes more robust than if one were to make a decision using just one decision tree. Under a balanced dataset, the algorithm predicts the PCOS risk factor with a success rate of about 83%.

6. RESULTS

The performance of the Random Forest model was very well balanced for both the classes of the data set. The Random Forest model scored a precision of 0.92, a recall of 0.97, and an f1-score of 0.94 for Class 0, meaning that it is well at predicting negative cases, hence, very few positive cases being misestimated, thereby indicating a good prediction strategy for negative cases. It had a precision of 0.97, a recall of 0.91, and

5.3 Decision Support and Prediction Output

Alternatively, there is also a PCOS risk predictor that will be provided by the system when we come across it, which will be categorized into pre-defined risk categories (high, low, and so forth). They will then be demonstrated on the frontend interface, after which it will be sent to the backend. This is because the system will provide interpretable results for them, which means that they will now be able to examine both the input and prediction parameters. This ensures the model acts as an aid in decision making and does not substitute a medical diagnosis.

F1-score of 0.94 for class 1 indicating very good results for positive cases whereas lower recall but higher precision for class 2. The model AUC ovr was fed into the Random Forest Classifier, which used 66% of the data as test dataset (to evaluate accuracy and prediction) and generated a overall accuracy of 94%. The precision, recall and F1- score values at both macro and weighted averages were similar (0.94), suggesting a balanced performance in all classes. It scored an excellent ROC AUC score of around 0.985 indicating a good ability to distinguish between the 2 classes.

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```
===== Random Forest =====
              precision    recall  f1-score   support

           0       0.92      0.97      0.94       300
           1       0.97      0.91      0.94       300

    accuracy                           0.94       600
   macro avg       0.94      0.94      0.94       600
weighted avg       0.94      0.94      0.94       600

ROC AUC: 0.9853444444444446
```

Fig.2 Results of Random Forest Classification Model

6.1 *Confusion Matrix*

Based on overall reasonable performance of Random Forest model, confusion matrix further shows the strength in terms of classification. A big chunk of predicted values are gained in diagonal band, indicating what we correctly predicted. In particular, 48.5% is true negatives and 46.0% is true positives, values consistent with the high accuracy and balanced F1-scores previously seen. The error rates are very low, having 1.5% of false-positives and 4.0% of false-negatives. Slightly higher missed positive case rate is consistent with lower recall value for class 1 (0.91), low false positive rate complements precision (0.97) however, such values come at the expense of a high false negative rates that we know could be detrimental to patients. All in all, the confusion matrix affirms that the model maintains a healthy balance of sensitivity and specificity, thus strengthening its reliability for PCOS prediction.

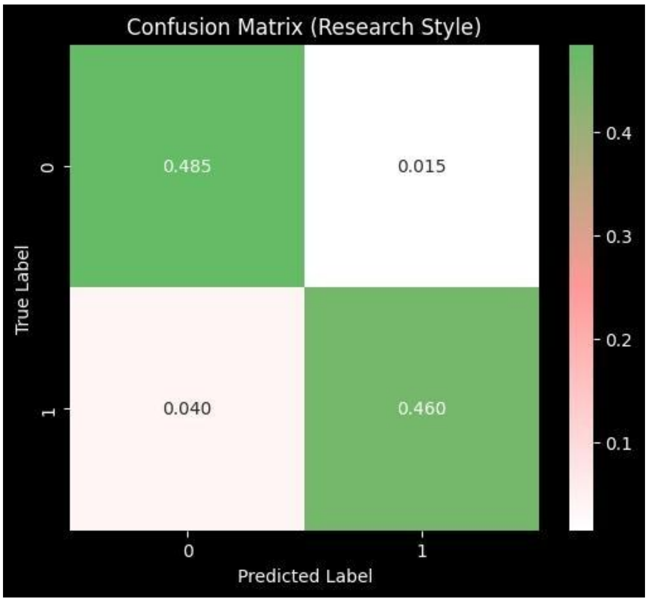

Fig.3 Confusion Matrix of Random Forest Model

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7. DISCUSSION

The new model, integrating real-time data collecting and machine learning, produces good candidate responses.[1] Early screening for polycystic ovary syndrome (PCOS). By combining user-provided clinical inputs, The System reduces dependency on expensive and time-consuming diagnostic processes with hardware-based measurements. By offering an affordable which the platform makes for a inexpensive, non-invasive first screening tool limited accessibility and proves to be helpful in environments with constrained resources. Then the automated prediction process jumps reducing time in clinical decision-making by minimizing the process needed for initial assessment. Therefore, the accuracy and The quality and completeness of the input data from an individual dictate how successful the results will be.

8. CONCLUSION

This study integrated embedded hardware, full- stack system design, and machine learning techniques to propose an innovative and non- invasive approach for the early detection of Polycystic Ovarian Syndrome (PCOS). The suggested system makes accurate and timely predictions by combining real-time physiological data collection with clinical inputs from the user. It does this by using a Random Forest classifier. The use of a queue-based mechanism makes it easier to run machine learning tasks that require a lot of computing power, while an asynchronous processing architecture ensures that data is handled well and can grow. The model works better when SMOTE is used for data balancing and feature selection techniques, with an accuracy of about 83%. The system demonstrates the integration of IoT-enabled data collection and machine learning for predictive healthcare applications. Further studies could include including more physiological parameters, increasing accuracy using sophisticated algorithms, and implementation of the technology in actual medical settings for validation.

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