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Hybrid Machine Learning Framework for Clinical Diagnosis of Polycystic Ovary Syndrome

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Abstract*: *Polycystic Ovary Syndrome (PCOS) is a common hormonal disorder in women, and it is difficult to diagnose at an early stage due to varying symptoms and limitations of traditional diagnostic methods. Early detection of PCOS is important to prevent long-term health complications. In this study, a hybrid machine learning model is proposed for PCOS detection using clinical and hormonal data. A dataset containing 541 patient records was used for analysis. Missing values were imputed using K-Nearest Neighbour (KNN), and the most relevant features were selected using Mutual Information. To address class imbalance, SMOTE was applied to the training data. Individual machine learning models were first evaluated, and based on their performance, a hybrid model was developed using a weighted soft-voting approach that combines Gaussian Naïve Bayes, Logistic Regression, and Random Forest. The experimental results suggest that the hybrid model strikes a better balance between accuracy, precision, and recall than any single model on its own. This makes it a more trustworthy approach for predicting PCOS. This project marks just the first phase of research, laying the groundwork for future studies that will combine these findings with ultrasound image analysis.

Keywords*: *Polycystic Ovary Syndrome, Hybrid Model, Random Forest, Support Vector Machines, Logistic Regression, SMOTE, Machine Learning, Ensemble Model, Medical Diagnosis.

Nomenclature:
PCOS: Polycystic Ovary Syndrome
AI: Artificial Intelligence
ML: Machine Learning
LR: Logistic Regression
GNB: Gaussian Naïve Bayes
SVM: Support Vector Machines
RF: Random Forest
SMOTE: Synthetic Minority Over-sampling Technique
KNN: K-Nearest Neighbour
DL: Deep Learning
CNNs: Convolutional Neural Networks
RBF: Radial Basis Function

I. INTRODUCTION

Polycystic Ovary Syndrome (PCOS) is one of the most prevalent hormonal disorders in women, affecting nearly one out of every ten women between the ages of 18 and 44 [2], [13]. Stein and Leventhal wrote the initial description of the illness in 1935. A hormonal imbalance causes PCOS, and it often comes with larger ovaries and, in some cases, several small cysts on the outer edge of the ovaries [2]. The word "polycystic" comes from the fact that these follicles are often seen on ultrasound. PCOS is also closely linked to insulin resistance, which makes it more likely that you may get metabolic illnesses like type 2 diabetes [4]. If PCOS is not found and treated quickly, it can lead to serious long-term concerns such as endometrial cancer, heart disease, and other ailments [4].

We see that doctors often use ultrasound scans, hormone tests and physical exams to diagnose PCOS [2] [12]. Many patients go through these tests. The tests can be annoying, time-consuming and can delay the diagnosis due to the varying symptoms and their overlap with other hormonal disorders [6] [15]. This has led researchers to explore machine learning methods that leverage data doctors already have to diagnose PCOS without procedures [5, 12]. The latest advancements in machine learning have demonstrated that models such as Naïve Bayes, Random Forest and Logistic work well for medical diagnosis.[3] [4] [5] [7].

Many recent studies that aim to predict PCOS rely on machine learning models and a simple evaluation pipeline. This can make the predictions look better than they really are [12, 15]. PCOS data have missing values, class imbalance, and heterogeneous symptom patterns, which make it hard for a model to generalise [6] [8] [18]. Hence, single-model approaches do not yield better results and lead to poor predictions and reduced trust in the setting. [15, 16].

We propose a hybrid machine learning approach that combines classifiers to leverage their collective strength and fill the gap. The hybrid machine learning approach aims to improve prediction accuracy, stability, and recall by adding learning methods, and it outperforms any model. The hybrid machine learning approach enables us to accurately and realistically evaluate PCOS detection performance using hormonal data.

The specific objectives of the study are:

- Investigate and understand the clinical features of polycystic ovary syndrome.
- To handle missing values and eliminate unnecessary features to preprocess the PCOS dataset.
- To use feature selection techniques to determine the most significant clinical features.
- To train and assess various machine learning models for the prediction of PCOS.
- To combine specific classifiers to create and

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execute a hybrid machine learning model.

This hybrid model combines the strengths of various machine learning methods, making it more accurate and stable than single-model approaches. It also provides a solid baseline. The hybrid model ensures that clinical features are strongly represented before learning-based ultrasound image analysis is added. The hybrid model builds a foundation for multimodal learning.

We set the foundation for the two-stage PCOS detection framework:

- This paper (**Hybrid Modelling Phase)** designs a hybrid machine learning model. The hybrid machine learning model uses the hormonal and clinical data to identify PCOS.
- The next paper (**Fusion Modelling Phase**) will combine the hybrid model with deep learning-based ultrasound image processing to create a multimodal fusion framework that will improve the diagnosis of PCOS.

II. REVIEW OF RELATED WORK

Due to its rising incidence and long-term health effects, Polycystic Ovary Syndrome (PCOS) has been extensively researched in recent years. Using clinical data, ultrasound images, or both, researchers have investigated machine learning (ML) and deep learning (DL) techniques to improve the precision and accuracy of PCOS diagnosis and enable earlier detection.

A. Deep Learning and Imaging Methods for PCOS diagnosis

Much research has looked into using medical imaging, specifically ultrasound pictures, to figure out if someone has polycystic ovarian syndrome. Convolutional Neural Networks (CNNs) are a deep learning method often used to extract features from ultrasound images of the ovaries automatically. These methods are quite accurate at identifying visual patterns associated with ovarian shape and follicle location. However, most image-based methods can't be used in clinical settings with limited resources because they require large labelled datasets and substantial computational power. Moreover, image-only techniques sometimes neglect critical hormonal and clinical indicators essential for the diagnosis of PCOS [1], [2], [10], [11], [17].

B. Machine Learning Models Using Clinical and Hormonal Data

Numerous researchers have shown that traditional machine learning algorithms utilise structured clinical and hormonal information to predict PCOS. Logistic Regression, Support Vector Machines, Decision Trees, Naïve Bayes, and Random Forests are among the most commonly used methods. These models are favoured because they are simple, easy to understand, and work well with medical data. Many Studies have found that Random Forest and SVM models frequently outperform linear models, especially when features exhibit non-linear correlations. But how well the model performs depends on the quality of the features, the preprocessing, and the dataset's balance [3], [4], [5], [6], [14], [19].

C. Feature Selection, Class Imbalance, and Data Preprocessing

PCOS datasets often have issues such as missing values, extra or irrelevant features, and an uneven number of PCOS and non-PCOS samples. Various studies have shown the significance of feature selection and resampling methods for improving predictive accuracy. Enhanced feature selection approaches help to make the model easier to understand and reduce noise. SMOTE and other techniques help to balance the dataset and increase recall for minority classes. Machine learning models often overfit or make poor predictions if you do not preprocess your data correctly [8], [12], [18].

D. Hybrid and Ensemble Machine Learning Approaches

New research shows that hybrid and ensemble machine learning models are better at finding PCOS than individual algorithms. Hybrid models take the best parts of several methods and combine them to produce more accurate, stable, and useful predictions in other situations. Both SVM and Logistic Regression have been used together in some studies, whereas Random Forest has been used with optimisation methods to reduce training error in others. These methods work best when the PCOS data include different symptom types and clinical trends. This is because a single model can be hard to train on different kinds of data [7], [15], [16], [20], [21], [22].

E. Multimodal Fusion Frameworks

Combining clinical data with ultrasound imaging has been the subject of a small but growing body of studies on multimodal detection of PCOS. Because they use both types of knowledge, these ways are better for diagnosing. Most of the time, these kinds of systems require a strong clinical or machine-learning foundation before they can use deep learning models, even though they show potential. This is why it's important to create a robust mixed clinical model that can serve as a foundation for future multimodal fusion frameworks [9], [13].

F. Identified Research Gap

A limited but growing body of research has looked at multimodal PCOS detection by combining clinical data with ultrasound imaging. These methods work better for diagnosing since they use both types of information. Even though these kinds of systems show promise, they usually require a solid clinical or machine-learning baseline before they can use deep learning models. This shows how important it is to build a strong hybrid clinical model that can serve as the basis for future multimodal fusion frameworks [12], [15], [21], [22].

III. METHODOLOGY

Using clinical and hormonal data, this study proposes a hybrid machine-learning framework for the early detection of Polycystic Ovary Syndrome (PCOS). Data preprocessing, feature selection, class balancing, model training, and hybrid ensemble learning make up the methodology. Training

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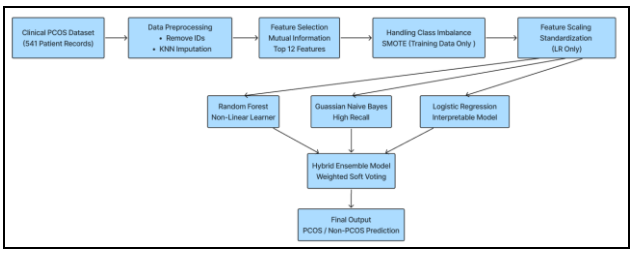
and testing data are separated throughout the pipeline to prevent data leakage and ensure accurate performance evaluation.



[Fig.1: System Architecture of PCOS Prediction Model]

A. Dataset

In this research, we used a publicly available clinical dataset on Polycystic Ovary Syndrome (PCOS) to construct and evaluate models. This dataset comprises medical records of women evaluated for PCOS based on clinical findings and laboratory results. In total, there are 541 patient records, out of which 177 are of women with PCOS and 364 are without PCOS. This imbalance is similar to what we see in real life, where the number of PCOS cases is very low compared to those diagnosed with PCOS.

Each patient record consists of different clinical, hormonal, physical, and lifestyle factors that are often used to determine if a person has PCOS or not. Some of the factors used include the number of follicles, the nature of the menstrual cycle (regular or irregular), hormone levels (LH, FSH), body measurements (BMI), and vital signs. The dataset contains both numerical and categorical variables, which makes it suitable for testing various machine learning and hybrid classification models for PCOS.

B. Data Preprocessing

Machine learning models often struggle when medical datasets contain numerical values. We did not delete records because doing so would have lost the data. Instead, we applied preprocessing to solve the problem and removed identifiers that were not relevant, such as "Sl." "No" and "Patient File No." because the identifiers do not help determine the diagnosis of PCOS. We also converted the factors written in format to numeric values so that the machine learning models can work correctly.

The K-nearest-neighbour (KNN) imputation approach was used to impute missing data. The K Nearest Neighbour (KNN) imputation approach guessed missing entries by looking at how similar patient records are in the feature space. The K Nearest Neighbour (KNN) imputation approach kept the data distribution and found local patterns in the dataset. So, the K-nearest-neighbour (KNN) imputation approach performed better on medical data than mean- or median-imputation methods.

C. Feature Selection

We used the Mutual Information (MI) method to select features that retain clinically important information while reducing the dimensionality. Mutual Information tells you how each feature connects to the target class, which makes it easier to locate the ones that give you the most helpful information for classifying PCOS. The MI ratings were computed only on the training dataset to prevent data leakage.

Based on the ML model's Mutual Information ranking of features, the Top 12 features were selected as the most informative: *Follicle No. (Left), Follicle No. (Right), Cycle Length (days), Cycle Regularity (R/I), AMH (ng/mL), PRL (ng/mL), Weight Gain (Y/N), Hair Growth (Y/N), Skin Darkening (Y/N), Fast Food Consumption (Y/N), Hip Circumference (inch), and Pulse Rate (bpm)*. The selection of this reduced set of features made the model more generalizable and easier to understand.

D. Handling Class Imbalance

In the dataset used in this research, there was a clear class imbalance, with fewer PCOS cases than non-PCOS cases. After conducting an in-depth analysis of existing research on PCOS prediction, it was observed that class imbalance is a major issue affecting model performance, particularly recall, which is essential for identifying true PCOS cases in medical diagnosis.

To address this problem, we applied the Synthetic Minority Over-Sampling Technique (SMOTE) to the training dataset. SMOTE generates synthetic samples for the minority class using existing PCOS cases. This balances the classes, ensuring there are as many minority-class data points as in the majority class. By using SMOTE, the classifiers learned from the minority class, thereby improving their recall.

E. Feature Scaling

Feature scaling was used to ensure that all selected features had the same influence on algorithms that are sensitive to the feature scaling. Standardisation was used to set all attributes to have a mean of zero and a variance of one. This helped to make our model training more stable and easier to converge. Only Support Vector Machine (SVM) and Logistic Regression models were scaled. These models are sensitive to changes in feature scale because they compute distances and perform gradient-based optimisation. Random Forest, on the other hand, is a tree-based machine learning algorithm that does not require feature scaling because its decisions are based on feature thresholds rather than distances. Selective feature scaling ensured that the tree-based models performed at their best while preserving their original structure.

F. Model Development

After performing data preprocessing, feature selection, class balancing, and scaling, several machine learning models were trained to predict Polycystic Ovary Syndrome (PCOS) from clinical and hormonal data. These models were selected based on the literature review of previous papers and their effectiveness for medical classification problems.

Four classifiers were selected for model development: Random Forest (RF), Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM), and Logistic Regression (LR). These models use different learning approaches, such as ensemble learning, probability-based classification, margin-based classification, and linear classification. Using different types of models helps us to capture various patterns in the PCOS dataset.

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i. Random Forest (RF)

Random Forest is an ensemble learning method that builds many decision trees using random subsets of data and features. Each decision tree makes its own prediction for the class label, and the final prediction is made by majority vote. This ensemble technique helps reduce the risk of overfitting and makes it easier to generalise compared to using a single decision tree. In this study, we used the Random Forest algorithm and trained it on a balanced dataset generated with SMOTE. The Top 12 features were used in this study. The model learned patterns in the number of follicles, hormone levels, and physical signs of PCOS. The model achieved a strong level of overall accuracy and consistency across evaluation metrics, making it suitable as a baseline classifier for predicting PCOS.

ii. Gaussian Naïve Bayes

Gaussian Naïve Bayes is a classifier based on a probabilistic model. It uses Bayes' Theorem for classification. The classifier assumes that, given the class label, the features are conditionally independent and normally distributed. Even with these basic assumptions, GNB performs better than expected on medical datasets.

For balanced training data, the recall rate of the Gaussian Naïve Bayes classifier for PCOS cases was quite impressive. This means the model found more PCOS cases and fewer false negatives. The algorithm learned probabilistic relationships among clinical features, such as hormone levels and cycle abnormalities, which improved its ability to predict PCOS.

iii. Support Vector Machines

The Support Vector Machine is a powerful classification method. It chooses the best decision boundary (hyperplane) that maximises the area between the classes. In this study, we used the Radial Basis Function (RBF) kernel as an example of a kernel function that SVMs use to handle non-linearly separable classes.

An RBF kernel-based SVM was trained using standardised feature values to keep the numbers constant. It was able to learn to discover non-linear correlations between the selected clinical features and to generate accurate classifications. SVM yielded balanced precision and recall scores, suggesting that it can reliably classify PCOS and non-PCOS patients.

iv. Logistic Regression

Logistic Regression is a widely used method for binary classification. It uses a logistic function to find out the probabilities of the outcome. While the model itself is very simple in architecture, its transparency makes it especially useful, especially for healthcare applications where "Black Box" decisions are typically viewed with suspicion.

Even with scaled and balanced data, our model was highly competitive against more complex methods. It was able to correctly model the linear relationship between PCOS and other clinical factors like hormones. Logistic Regression is a simple and reliable method for medical diagnosis because it has high accuracy and recall.

G. Hybrid Model Building

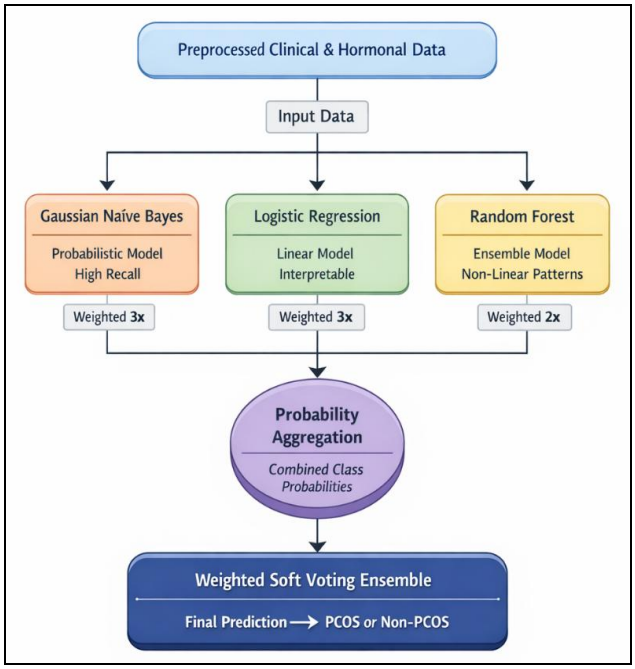
In this research, we have built a Hybrid Machine Learning Model to improve the accuracy and prediction performance of PCOS detection by combining multiple classifiers and their respective features. This hybrid approach combines probabilistic, linear, and non-linear learning mechanisms. Instead of depending on a single algorithm, it allows the model to identify different types of patterns in clinical and hormonal data.

The base learners selected for the hybrid model were Gaussian Naive Bayes (GNB), Logistic Regression (LR), and Random Forest (RF). The selection of these models was based on the performance of each classifier individually and the literature about them. These models were chosen because each addresses a different aspect of PCOS prediction. Gaussian Naïve Bayes performs well with medical datasets and has a high recall rate. Logistic Regression is easy to understand and has clear decision boundaries. Random Forest is good at identifying non-linear correlations in the data and can handle complex relationships among variables.

H. Hybrid Model Architecture

The hybrid model was built using the soft-voting ensemble method, which aggregates the outputs of individual classifiers as probability distributions rather than hard class labels. This is done using a weighted average, in which the probabilities of the individual classifiers are combined, and the class with the highest probability is selected as the final prediction.

Weighted voting was used to indicate how much each classifier contributed, based on its performance in practice. Gaussian Naïve Bayes and Logistic Regression were assigned greater weight because their findings were consistently reliable. Random Forest was assigned a slightly lower weight to serve as a supporting non-linear learner in the ensemble.



[Fig.2: Proposed Hybrid Machine Learning Model Architecture for PCOS Detection]

I. Experimental Setup

To evaluate the machine learning and hybrid models, we designed a structured

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experiment using the cleaned clinical dataset. We split the data into an 80% training set and a 20% testing set to ensure the models were validated on strictly unseen data. We addressed class imbalance by applying the Synthetic Minority Over-Sampling Technique (SMOTE), ensuring this was done only on the training fold to prevent data leakage. Feature standardisation was applied specifically to Logistic Regression and Support Vector Machine (SVM), due to their sensitivity to feature magnitudes, whereas tree-based models were trained on unscaled data.

We established a baseline by training four distinct models: Gaussian Naïve Bayes (GNB), Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM), under identical conditions. We then developed a hybrid model that integrated GNB, LR, and RF via a weighted soft-voting ensemble. This approach was developed to leverage each classifier's strengths.

Performance of the model was evaluated based on the following metrics:

Accuracy: the model's correctness.

Precision: This refers to the correctness of the positive diagnosis of PCOS.

Recall: the model's ability to recognise the actual positive cases.

F-1 score: This is the combination of precision and recall and is also called the harmonic mean.

IV. RESULTS AND FINDINGS

In this section, the results obtained using individual machine learning models and the proposed hybrid model for PCOS prediction are presented. All models were evaluated using the same train-test split and performance metrics to provide a fair and unbiased comparison.

A. Performance of Individual Machine Learning Models

Four machine learning models, namely Gaussian Naïve Bayes (GNB), Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM), were trained on the selected top 12 clinical features after preprocessing, feature selection, and class balancing using SMOTE.

Table I: Performance Comparison of Individual Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Random Forest	89.91	85.71	83.33	84.51
Gaussian Naïve Bayes	92.66	85.00	94.44	89.47
Logistic Regression	90.83	86.11	86.11	86.11
Support Vector Machine	90.83	86.11	86.11	86.11

From Table I, Gaussian Naïve Bayes achieved the highest recall, indicating a strong ability to identify PCOS cases correctly. This is particularly important in medical diagnosis, where missing a positive case can have serious clinical consequences. Logistic Regression and Support Vector Machine produced stable and comparable results because, after feature selection and scaling, the data became nearly linearly separable. In such cases, both models tend to learn similar decision boundaries, resulting in nearly identical performance across evaluation metrics. Random Forest effectively captured non-linear relationships in the data but showed slightly lower recall than Gaussian Naïve Bayes, as it prioritises overall classification accuracy over sensitivity to the minority class.

These observations guided the selection of base learners for the proposed hybrid model.

B. Confusion Matrix Analysis of Individual Models

The confusion matrices show the true positive, true negative, false positive, and false negative values for each model. Gaussian Naïve Bayes showed fewer false negatives than other models, confirming its high recall. This is very important for the detection of medical diagnoses like PCOS, where the number of missed positive cases must be low. Reducing the number of false negatives is critical in PCOS diagnosis, as this disease may have long-term consequences if its detection is delayed.

Table II: Confusion Matrix Analysis of Individual Models

Model	True Negatives (TN)	False Positives (FP)	False Negatives (FN)	True Positives (TP)
Random Forest	68	5	6	30
Gaussian Naïve Bayes	67	6	2	34
Logistic Regression	68	5	5	31
Support Vector Machine	68	5	5	31

C. Performance of the Proposed Hybrid Model

To improve the reliability and accuracy of PCOS prediction, we developed a hybrid machine learning model that combines multiple classifiers, each with its own strengths. Based on the performance of individual models and insights from experimental analysis, Gaussian Naïve Bayes (GNB), Logistic Regression (LR), and Random Forest (RF) have been selected as the base classifiers for developing the proposed hybrid model.

Table III: Performance of the Proposed Hybrid Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Hybrid Model (GNB + LR + RF)	92.66	86.84	91.67	89.19

The proposed hybrid machine learning model achieved high prediction accuracy and provided a better balance between precision and recall without compromising overall accuracy. The proposed model also effectively utilised a weighted soft-voting strategy to combine the individual classifiers' advantages, allowing the stronger model to exert greater influence on the prediction results. This ensemble approach made the model more stable and reduced the limitations of the single classifier method.

D. Confusion Matrix Analysis of Hybrid Model

The hybrid model resulted in fewer false-negative cases, which is important, especially in medical diagnosis, where missing a single case of PCOS can delay treatment. At the same time, false-positive cases were kept to a minimum to ensure that non-PCOS cases were correctly classified.

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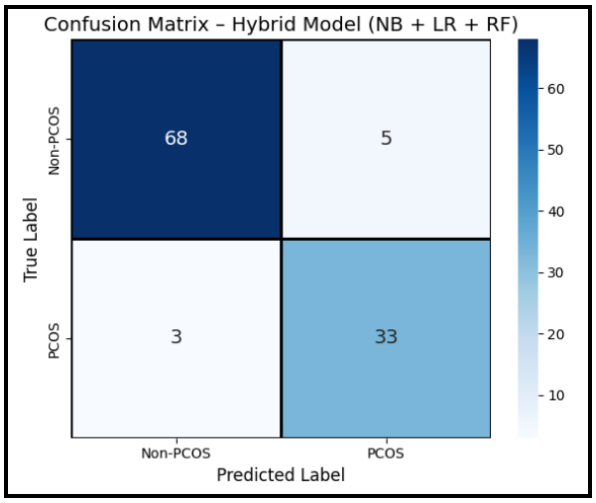
This shows that the proposed approach is reliable and can be used in medical diagnosis systems.

It is observed that, when compared with individual machine learning models, the proposed hybrid approach is more stable and reliable across all evaluation metrics. Though the Gaussian Naïve Bayes approach performed very well in recall, the proposed approach also improved precision, making it more stable and reliable for predicting PCOS.



[Fig.3: Confusion Matrix of Hybrid Model]

V. DISCUSSIONS

The results of the experiment show that the predictive performance of PCOS varies across different machine learning models. Among all classifiers, Gaussian Naïve Bayes has the highest recall, indicating a strong ability to identify cases of PCOS correctly. The recall value is very important, especially in medical diagnosis, as failing to detect a case of PCOS may lead to health risks if proper treatment is delayed. Logistic Regression and Support Vector Machine showed similar results because, after feature selection and scaling, the dataset became nearly linearly separable; hence, the two classifiers learned the same decision boundaries. The Random Forest Classifier captured the non-linear relationships well; hence the overall accuracy was quite good. However, the recall was slightly lower than that of the Gaussian Naïve Bayes Classifier.

The KNN-based imputation method maintained the clinical patterns at the patient level. At the same time, the SMOTE-based balancing of the training set addressed the class imbalance, yielding 291 PCOS cases and 291 non-PCOS cases. This improved the recall of all the models. The Mutual Information-based feature selection method reduced the number of features to 12, which are clinically important, thereby improving model generalisation and preventing overfitting.

The proposed hybrid model (GNB + LR + RF) achieved an accuracy of 92.66%, a precision of 86.84%, a recall of 91.67%, and an F1 Score of 89.19%, indicating that it outperformed the individual models. Although the individual model, Gaussian Naïve Bayes, achieved the highest recall, the hybrid model maintained high sensitivity, precision, and stability. In addition, the hybrid model's confusion matrix showed fewer false negatives than those of the individual models, indicating that it is well-suited for clinical decision support systems. The results indicate that the weighted ensemble learning method is a more reliable and robust diagnostic method for predicting PCOS than the individual models.

VI. FUTURE SCOPE

The proposed hybrid machine learning model, developed using clinical and hormonal data, provides a strong and reliable foundation for PCOS detection. As an extension of the proposed model, the framework could be improved by integrating ultrasound images using deep learning techniques, such as Convolutional Neural Networks (CNNs). Ultrasound images provide useful visual information about ovarian morphology, which can support clinical data and further improve diagnostic performance.

Using a multimodal fusion technique that combines machine-learning-based clinical predictions with deep-learning-based image analysis would help increase the system's reliability and reduce false-negative cases. This kind of technique will help increase the accuracy and reliability of PCOS detection systems and also create a more effective decision support system in real-world settings.

VII. CONCLUSION

In this study, we developed a hybrid machine-learning model to detect Polycystic Ovary Syndrome (PCOS) early by analysing clinical and hormonal data. For this purpose, a wide range of techniques were used, including preprocessing, KNN imputation for handling missing values, feature selection using mutual information, and class balancing using SMOTE.

During the testing phase, it was also observed that each model performed better in certain aspects: the Gaussian Naïve Bayes model had high recall, while the others offered overall stability. To benefit from this, a weighted soft-voting mechanism was used to combine Random Forest, Gaussian Naïve Bayes, and Logistic Regression into a single model.

The hybrid approach also showed higher stability than using a single classifier, achieving an accuracy of 92.66%, a recall of 91.67%, and an F1 score of 89.19%, thereby demonstrating greater stability. As shown in the confusion matrix (Fig. 3), the model successfully reduced the number of false-negative cases. This is a major improvement for medical diagnostics, as a missed positive case may delay necessary treatment. Our results show that ensemble learning is a more reliable approach for medical diagnosis. This research provides a strong foundation for our future work, especially our plan to integrate deep learning analysis of ultrasound images into a multi-modal detection approach.

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

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organizations or agencies. This independence ensures that the research is conducted objectively and free from external influence.

- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** Each author has individually contributed to the article. Fatima Khan Sarguroh conceptualised the hybrid model, developed and implemented the model, conducted experiments and analyses, and wrote the manuscript. Srivaramangai R. supervised the research work, provided methodological guidance, reviewed the results, and approved the final manuscript.

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