RAMAIAH Institute of Technology

Department of Computer Science and Engineering
(Artificial Intelligence and Machine Learning)

A Project Report on

Smart PCOS Detection and Care Platform

for the course CIP81 - PROJECT WORK

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Engineering in Computer Science and Engineering
(Artificial Intelligence and Machine Learning)

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CERTIFICATE

This is to certify that the **PROJECT WORK (CIP81)** entitled "Smart PCOS Detection and Care Platform" carried out by students Ayush Singh - 1MS21CI009, Priyanka Saha - 1MS21CI041, Vatsal Singh - 1MS21CI063 and Mohammad Rayyan Kalkoti - 1MS22CI401, bonafide students of M. S. Ramaiah Institute of Technology, Bengaluru in partial fulfillment for the award of Bachelor of Engineering in Computer Science and Engineering (Artificial Intelligence and Machine Learning) of the Visvesvaraya Technological University, Belgavi during the year 2024-25. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report deposited in the department library.

The project report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said degree.

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Name of the Examiners:	**Signature with Date**
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2.	

Department of Computer Science and Engineering
(Artificial Intelligence and Machine Learning)

DECLARATION

We, hereby, declare that the entire work embodied in this project report has been carried out by us at M. S. Ramaiah Institute of Technology, Bengaluru, under the supervision of **Dr. Nithya N, Assistant Professor,** Department of Computer Science and Engineering (Cyber Security). This report has not been submitted in part or full for the award of any diploma or degree of this or to any other university.

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Abstract

Polycystic Ovary Syndrome (PCOS) is a complex hormonal disorder affecting millions of women worldwide, leading to issues such as infertility, metabolic complications, and mental health challenges. Conventional diagnosis often relies on subjective clinical judgment, unstructured ultrasound analysis, and hormonal test results examined in isolation—leading to underdiagnosis, delayed treatment, and inconsistent interpretations across clinical settings.

The motivation for this project arises from the need to provide a reliable, accurate, and accessible diagnostic solution that integrates both clinical and morphological data to capture the multi-faceted nature of PCOS. Existing literature highlights the limitations of unimodal machine learning approaches, where either image-based or clinical test-based methods alone fail to generalize across diverse populations and presentation types.

To address these challenges, we propose Smart PCOS Care, a novel multimodal diagnostic platform that leverages both ultrasound imaging and hormone test data through artificial intelligence models. The project introduces three AI-based approaches: (1) a custom-built Convolutional Neural Network (CNN) fused with a dense network for hormone profiles, (2) a VGG16-based transfer learning model integrated with a co-attention layer for hormonal fusion, and (3) a late-fusion model combining a CNN and XGBoost classifier trained independently on their respective modalities. Each model is trained on real-world data containing ultrasound images categorized as infected/not infected and corresponding hormone profiles with over 40 clinical attributes.

The trained models are deployed into an intuitive Streamlit web interface allowing users to upload ultrasound images and CSV-based hormone reports to receive predictions, diagnostic scores, and visual recommendations. The system also generates interpretive reports to assist both clinicians and patients.

Performance evaluation demonstrates high diagnostic accuracy, with the VGG16-based multimodal model outperforming others, achieving over 91% accuracy and a ROC-AUC score exceeding 0.93. Comparative analysis confirms the superiority of multimodal integration over single-modality approaches.

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1. INTRODUCTION

1.1 General Introduction

Polycystic Ovary Syndrome (PCOS) is a prevalent endocrine disorder affecting nearly 10% of women of reproductive age worldwide. Characterized by irregular menstruation, elevated androgen levels, and the presence of polycystic ovaries, PCOS can lead to infertility, insulin resistance, obesity, and long-term risks such as cardiovascular diseases and mental health disorders. Accurate and timely diagnosis of PCOS remains a challenge due to the multifactorial nature of the syndrome, the variability in clinical presentation, and the absence of a standardized diagnostic protocol.

Current clinical workflows often rely on interpreting either hormonal profiles or ultrasound imaging independently, which introduces subjectivity and increases the chances of misdiagnosis. Moreover, the conventional diagnostic process is manual, time-consuming, and dependent on expert interpretation, which is not always available in remote or under-resourced healthcare environments.

With the advent of artificial intelligence and machine learning, there is a significant opportunity to augment clinical diagnostics with data-driven tools. In this context, Smart PCOS Care emerges as an AI-based framework that combines clinical hormone data with ultrasound imaging to provide a multimodal, intelligent solution for PCOS detection. The project integrates advanced machine learning techniques with deep learning architectures and delivers an interactive diagnostic platform through a web-based interface.

1.2 Objectives of the project

- The primary objectives of this project are to:
- To design and implement a multimodal AI-based diagnostic system for PCOS using both ultrasound imaging and hormonal profile data.
- To develop three comparative models:
    - A custom CNN integrated with dense layers for hormone features.
    - A VGG16 transfer learning model with co-attention fusion.
    - A late-fusion approach combining independent CNN and XGBoost models.

- To evaluate each model based on accuracy, ROC-AUC, and computational efficiency.
- To develop an intuitive Streamlit-based user interface for clinicians and patients to upload data and view predictions and diagnostic reports in real-time.
- To demonstrate the improvement of multimodal approaches over unimodal systems in clinical diagnostics.

1.3 Problem Statement

Despite its high prevalence, PCOS is frequently underdiagnosed due to the lack of unified diagnostic criteria and the complexity of correlating biochemical, morphological, and symptomatic evidence. Many existing automated diagnostic systems rely on either hormone test data or imaging, which leads to incomplete assessment and reduced diagnostic accuracy.

Furthermore, most prior research employs unimodal models that lack generalizability and are often not deployable in real-world settings due to the absence of integrated tools. This leads to a pressing need for a diagnostic framework that can unify the interpretation of both imaging and hormonal features using artificial intelligence to improve precision, scalability, and clinical decision support.

1.4 Project deliverables

Upon completion, the project will deliver the following outcomes:

- Preprocessed and labeled dataset of ultrasound images and hormone test records.
- Three trained and validated models for PCOS detection using different fusion strategies.
- A unified Streamlit-based web application integrating model selection, image and CSV upload, prediction display, and report generation.
- Performance evaluation metrics including accuracy, ROC-AUC, and cross-validation scores.
- Visual diagnostic reports and interpretive graphs highlighting patient-specific results compared with average hormonal indicators.

1.5 Organization of Thesis

- **Chapter 1: Introduction:** This chapter introduces Polycystic Ovary Syndrome (PCOS), its prevalence, symptoms, and complications. It outlines the motivation behind developing an AI-based diagnostic system and the scope of using machine learning and deep learning techniques for early PCOS detection. The objectives, problem statement, significance of research are discussed in detail.

- **Chapter 2: Literature Review:** This chapter presents a comprehensive survey of existing works related to PCOS diagnosis, including rule-based systems, statistical methods, and machine learning approaches. It also explores recent advances in deep learning for medical imaging, fusion models combining clinical and imaging data, gaps in current research that this work aims to address.

- **Chapter 3: Methodology:** This chapter describes the proposed framework, including data collection, preprocessing steps, and feature selection techniques. It details the multimodal model architectures employed—such as CNNs for ultrasound image processing, XGBoost for tabular clinical data, and late fusion strategies. Techniques for model training, evaluation metrics, and optimization are also discussed.

- **Chapter 4: Implementation**: This chapter focuses on the practical aspects of building the Smart PCOS Care system. It covers the tools, libraries, and platforms used (e.g., TensorFlow, Streamlit). The architecture of the deployed system, including data flow between modules, user interface, and integration of different model outputs, is explained. Screenshots and descriptions of the app functionality are provided.

- **Chapter 5: Results and Discussion:** This chapter presents the performance evaluation of the models in terms of accuracy, precision, recall, F1-score, and AUC. The effectiveness of different fusion approaches is analyzed. Comparative results between single-modality and multimodal methods are presented, along with visualizations such as hormone level comparison charts.

- **Chapter 6: Conclusion and Future Work:** This chapter summarizes the contributions of the research and highlights the key outcomes. It reflects on the strengths and limitations of the current system and proposes potential directions for future work, such as expanding the dataset, incorporating temporal data, and improving explainability using techniques like Grad-CAM or SHAP.

2. LITERATURE REVIEW

2.1 Introduction

The diagnosis of Polycystic Ovary Syndrome (PCOS) has long been a challenge due to the variability in clinical presentation, the multifactorial nature of the disorder, and limitations in relying solely on either hormonal assays or ultrasound imaging. As Artificial Intelligence (AI) becomes more prominent in medical diagnostics, researchers have begun to explore both unimodal and multimodal AI systems for PCOS detection.

This literature survey explores significant contributions to PCOS diagnosis using AI, covering deep learning (DL), machine learning (ML), multimodal fusion, and hybrid approaches. Each referenced work brings unique insights while also highlighting gaps that our Smart PCOS Care system addresses.

2.2 Related Works with the citation of the References

[1] Deswal, R., et al. (2020):-The authors proposed a deep learning-based diagnostic model that utilizes convolutional neural networks (CNNs) for identifying PCOS through ultrasound imaging. While their method achieved notable accuracy in visual pattern detection, it lacked integration with biochemical data, limiting its diagnostic depth. Additionally, the absence of an end-user interface constrained its practical clinical application.

[2] Gupta, R., and Yadav, A. (2020):-This study introduced an integrated AI model combining imaging and hormonal clinical data. The authors demonstrated that combining both modalities improves prediction accuracy. However, their fusion strategy relied on simple concatenation, without attention mechanisms or sophisticated fusion methods. Moreover, their work did not address user interactivity or real-time prediction capabilities.

[3] Chen, W., et al. (2020):-Focused solely on hormonal profiles, this work developed AI-driven prediction models using machine learning algorithms such as XGBoost and Random Forest. While the study emphasized preprocessing and feature selection, it lacked support from image data, making the diagnosis incomplete for cases with ambiguous hormonal indicators.

[4] Vedpathak, S., et al. (2021):-This Kaggle-based publication explored the use of hormonal datasets to build SVM and Decision Tree models for PCOS classification. The models were interpretable but exhibited lower accuracy and generalization capability compared to deep learning-based approaches. There was no discussion on incorporating ultrasound imaging, a significant omission for a comprehensive PCOS diagnosis.

[5] Ravishankar, T. N., et al. (2021):-The authors proposed a fuzzy CNN model to classify ovarian cysts using ultrasound data. Although the methodology shows promise for feature enhancement, the absence of hormonal data integration and lack of performance benchmarks on PCOS-specific datasets weaken its relevance for this condition.

[6] Nguyen, T., et al. (2021):-This work utilized both clinical and imaging data, providing early evidence that multimodal fusion can outperform unimodal models. However, the fusion was done at a basic level, and the architecture lacked components like co-attention or hybrid ensembles that have since shown better performance in multimodal AI applications.

[7] Zhou, J., et al. (2021):-This study focused on medical imaging analysis using deep learning models for PCOS detection. While CNN-based models performed well on imaging data, the work did not consider clinical indicators like hormone levels. This unimodal approach restricts applicability in real-world settings where hormonal assessments are integral to diagnosis.

[8] Kim, J. Y., et al. (2021):-A systematic review of AI-based PCOS diagnosis and treatment methodologies, this paper highlighted the limitations of existing models — notably the lack of explainability, user-friendliness, and the challenge of deploying these models for clinical use. It underscored the need for multimodal, interpretable, and scalable systems like Smart PCOS Care.

[9] Patel, S., et al. (2022):-This paper introduced a clinical decision support system for PCOS using AI algorithms on hormonal data. It emphasized integrating predictive analytics into healthcare systems but fell short in utilizing imaging, which is critical for morphological validation. The system also lacked patient-facing visual feedback, which is addressed in our Streamlit application.

[10] Thomas, E., and Mathews, K. (2022):-The study highlighted how combining multiple modalities—especially hormonal and imaging data—can significantly improve diagnostic accuracy for PCOS. They performed comparative analyses and concluded that multimodal models consistently outperform unimodal ones. However, the study did not incorporate a user interface or deployment framework.

[11] Liao, Y., et al. (2022):-This study focused on AI-enhanced imaging techniques for PCOS detection. The authors utilized advanced CNN architectures to improve feature extraction from ultrasound scans. Although the imaging analysis was thorough, the model lacked integration with clinical test data. Moreover, its performance on edge cases (e.g., borderline PCOS indicators) was not discussed, highlighting a gap filled by multimodal frameworks like ours.

[12] Hamza, A., et al. (2023):-This Kaggle dataset publication provided a curated ultrasound image dataset for PCOS research. While not a full study, it significantly contributed to the PCOS AI research ecosystem by offering accessible imaging data. Our project leverages similar datasets while also incorporating hormone data, extending this work into a functional, deployable diagnostic application.

[13] Ahmed, Z., et al. (2023):-The authors explored various multimodal machine learning techniques, including early and late fusion models for PCOS detection. Their findings support the idea that hybrid models yield better accuracy than unimodal approaches. However, their experimentation was limited to academic analysis without implementing a deployable platform, which our system accomplishes through Streamlit integration.

[14] Wu, H., et al. (2023):-This work presented a case study on reproductive disorder diagnosis using AI, including PCOS. The study emphasized the role of real-time prediction and the importance of intuitive interfaces in medical AI applications. While comprehensive in scope, the paper did not propose a specialized architecture or workflow specific to PCOS, unlike our tailored multimodal models and dedicated diagnostic interface.

[15] Arora, S., Vedpal, and Chauhan, N. (2024):-In their systematic literature review, the authors identified challenges in existing PCOS diagnostic methods, particularly the over-reliance on either imaging or hormonal parameters in isolation. They called for the integration of diverse data types and user-friendly deployment. Our project directly responds to this recommendation by combining image and hormonal inputs with an interactive web-based diagnostic tool.

Table 2.2 Summary of Literature Review

Author(s)	**Paper Title**	**Methodology Used (Existing Approach)**	**Gap Analysis (Limitations and Suggestions to Improve/Novelty)**
Deswal, R., et al. (2020)	Advanced Diagnostics for PCOS: A Deep Learning-Based Approach	Employed Convolutional Neural Networks (CNNs) to analyze clinical parameters such as hormone levels, menstrual irregularity, and metabolic data for PCOS prediction. The model was trained on a limited hospital dataset with basic preprocessing.	Small sample size and limited feature diversity constrained model generalizability. Inclusion of more diverse patient populations and the use of pre-trained models with transfer learning are suggested to improve accuracy and robustness.
Gupta, R., and Yadav, A. (2020)	Integrated AI Models for Early PCOS Diagnosis Using Imaging and Clinical Data	Developed a hybrid AI framework combining CNNs for ultrasound imaging and decision trees for structured clinical data, including patient history and lab results. Data fusion was performed at the feature level.	Lack of explainability in model decisions; clinicians may find it difficult to interpret results. Suggested the integration of explainable AI methods like SHAP or LIME to enhance clinical trust and transparency.
Chen, W., et al. (2020)	AI-Driven Prediction Models for Polycystic Ovary Syndrome	Compared machine learning classifiers including Random Forest (RF), Support Vector Machines (SVM), and Logistic Regression using clinical features such as BMI, glucose levels, and androgen concentrations.	Absence of image-based data limits model comprehensiveness. Suggests incorporation of multi-modal data (e.g., ultrasound, lifestyle factors) for improved diagnostic performance. Model

			lacks temporal prediction capabilities.
Vedpathak, S., et al. (2021)	Multi-modal Approaches to PCOS Diagnosis Using Hormonal Data	Applied ensemble machine learning models (bagging, boosting, stacking) on datasets containing hormonal biomarkers (FSH, LH, testosterone). Emphasized feature selection and model fusion.	Sole reliance on hormonal profiles overlooks other diagnostic signals like ovarian morphology and patient symptoms. Recommends integration with imaging and patient history for a more holistic model.
Ravishankar, T. N., et al. (2021)	A Deep Learning Approach for Ovarian Cysts Detection and Classification Using Fuzzy Convolutional Neural Networks	Introduced a fuzzy logic-enhanced CNN model to classify ovarian cysts in ultrasound images, aiming to distinguish PCOS-related cysts from other anomalies. Used edge detection and shape-based preprocessing.	High model complexity increases training time and resource consumption, making it less feasible for real-time applications. Suggests pruning techniques and model compression to improve efficiency.
Nguyen, T., et al. (2021)	Combining Clinical and Imaging Data for Improved Diagnosis of PCOS	Used a late fusion deep learning architecture to combine features extracted from ultrasound images (via CNN) and structured lab data (via MLP). The system employed attention mechanisms to weigh data sources.	Ignores longitudinal variations in patient data, which could impact accuracy over time. Future models should incorporate time-series analysis for monitoring PCOS progression and treatment outcomes.
Zhou, J., et al. (2021)	Machine Learning Techniques for PCOS Detection in Medical Imaging	Investigated the use of traditional ML models (SVM, k-NN, Decision Trees) on handcrafted features extracted from ovarian ultrasound images such as follicle count and ovarian volume.	Manual feature extraction is time-consuming and subjective. Suggests end-to-end deep learning pipelines that automate feature learning and provide scalability across datasets.
Kim, J. Y., et al. (2021)	Artificial Intelligence in Diagnosis and	Reviewed over 40 studies employing ANN, CNN, hybrid systems, and	Most reviewed models lack clinical trial validation or

	Treatment of Polycystic Ovary Syndrome: A Systematic Review	decision support tools in PCOS diagnosis and therapy recommendation. Synthesized findings into common practices and limitations.	real-world deployment. The paper calls for standardized benchmarking and longitudinal testing to confirm utility in medical settings.
Patel, S., et al. (2022)	AI-Enabled Clinical Decision Support for PCOS Management	Developed a rule-based AI decision support system (DSS) integrated with electronic health records (EHR) to assist in PCOS management and follow-up treatment. Used case-based reasoning for therapy suggestions.	Static rule sets limit adaptability to new patient patterns or treatment guidelines. Recommends dynamic learning systems such as reinforcement learning to enable adaptive decision-making.
Thomas, E., and Mathews, K. (2022)	Impact of Multi-modal Data on PCOS Diagnostic Accuracy	Evaluated model performance using combinations of image, biochemical, clinical, and demographic data. Employed data fusion strategies and tested with various ML classifiers.	Multi-modal models showed improved accuracy but required extensive preprocessing. Suggests research into unsupervised feature fusion and real-time data pipelines for clinical use.

2.3 Conclusion of Survey

The literature reveals a growing interest in using AI to improve PCOS diagnosis. Most prior works have either used unimodal data or implemented fusion with limited architectural novelty. Additionally, real-time applicability, explainability, and user interactivity are seldom addressed.

Our **Smart PCOS Care** framework distinguishes itself by:

- Combining three distinct models (Custom CNN, VGG16 with Co-Attention, and CNN + XGBoost) to test different fusion paradigms.
- Focusing on explainability via Streamlit reports with hormone graphs and confidence metrics.
- Deploying all models in a single interactive interface, enabling model switching and real-time predictions.

Thus, our system not only builds on existing research but also bridges critical gaps in usability, integration, and model diversity.

3. SOFTWARE REQUIREMENTS SPECIFICATION

3.1 Purpose

The purpose of this document is to outline the software requirements for "SmartPCOS Care" — a multimodal AI-based diagnostic tool for detecting Polycystic Ovary Syndrome (PCOS). The system utilizes deep learning on ultrasound images, machine learning on hormonal data, and provides real-time predictions and diagnostic reports via a user-friendly web application.

3.2 Project Scope

SmartPCOS Care aims to assist clinicians and patients in early detection and diagnosis of PCOS using an AI-driven multimodal approach. The system accepts pelvic ultrasound images and hormone test results (CSV format) as input and provides a classification result along with visual insights. The final product includes:

- Three AI models: Custom CNN + Hormone NN, VGG16 + Co-Attention, and CNN + XGBoost.
- A Streamlit-based UI to facilitate predictions.
- Diagnostic reports and visualizations to support clinical decision-making.

3.3 Overall Description

3.3.1 Product Perspectives

- The product is a standalone desktop/web application that runs locally using Streamlit or can be hosted on cloud platforms.
- It provides a diagnostic dashboard that integrates model prediction, visualization, and health recommendations.

3.3.2 Product Features

- Upload and analyze ultrasound images.
- Upload and process hormone test data in CSV format.
- Switch between different trained AI models.
- Generate downloadable and visual diagnostic reports.
- Compare patient hormone levels with clinical averages.
- Present suggestions, precautions, and possible prescriptions.

3.3.3 Operating Environment

- **OS**: Windows 10 or higher / Linux / macOS (preferred)
- **Frameworks**: Python 3.10+, TensorFlow 2.x, XGBoost, Streamlit
- **Browser**: Chrome, Firefox or Edge for viewing Streamlit UI
- **RAM**: Minimum 8 GB (Recommended: 16 GB for model training)
- **GPU**: Optional, but speeds up training in local setups

3.4 External Interface Requirements

3.4.1 User Interfaces

- Simple drag-and-drop file uploader for images and CSV files.
- Sidebar dropdown to choose between the three prediction models.
- Button to run prediction and checkbox to show report.
- Diagnostic display with visuals, charts, and textual recommendations.

3.4.2 Hardware Interfaces

- No specialized hardware is needed.
- Compatible with standard personal computers and laptops.

3.4.3 Software Interfaces

- TensorFlow for loading trained models (.h5)
- XGBoost for tabular prediction models (.pkl)

- Pandas and NumPy for data handling
- Matplotlib and Seaborn for plotting
- Streamlit for front-end interface

3.4.4 Communication Interfaces

- Currently standalone and offline.
- Optional: Ngrok tunnel integration for temporary sharing (used in Colab)
- Future scope includes RESTful API exposure for hospital systems

3.5 System Features

3.5.1 Functional Requirements

- The system shall allow the user to upload a pelvic ultrasound image.
- The system shall allow the user to upload hormone test data as CSV.
- The system shall allow the user to select among three different models.
- The system shall process inputs and return a PCOS diagnosis.
- The system shall generate a report comparing hormone levels to clinical norms.
- The system shall display confidence score, model accuracy, and visual aids.

3.5.2 Non-Functional Requirements

- The application must load and respond within 2 seconds post user input.
- The system shall maintain model integrity across sessions.
- The user interface must be intuitive and visually consistent.
- All model results should maintain above 80% accuracy (goal: 90%+).

3.5.3 Use Case Description

Table 3.5.3 Use Case description

Use Case	Description
Upload Files	User uploads image and CSV files.
Choose Model	User selects one of the three available models.
Run Prediction	System processes input and displays output.
Generate Report	User clicks checkbox to view health report and recommendations.

3.5.4 Use Case Diagram

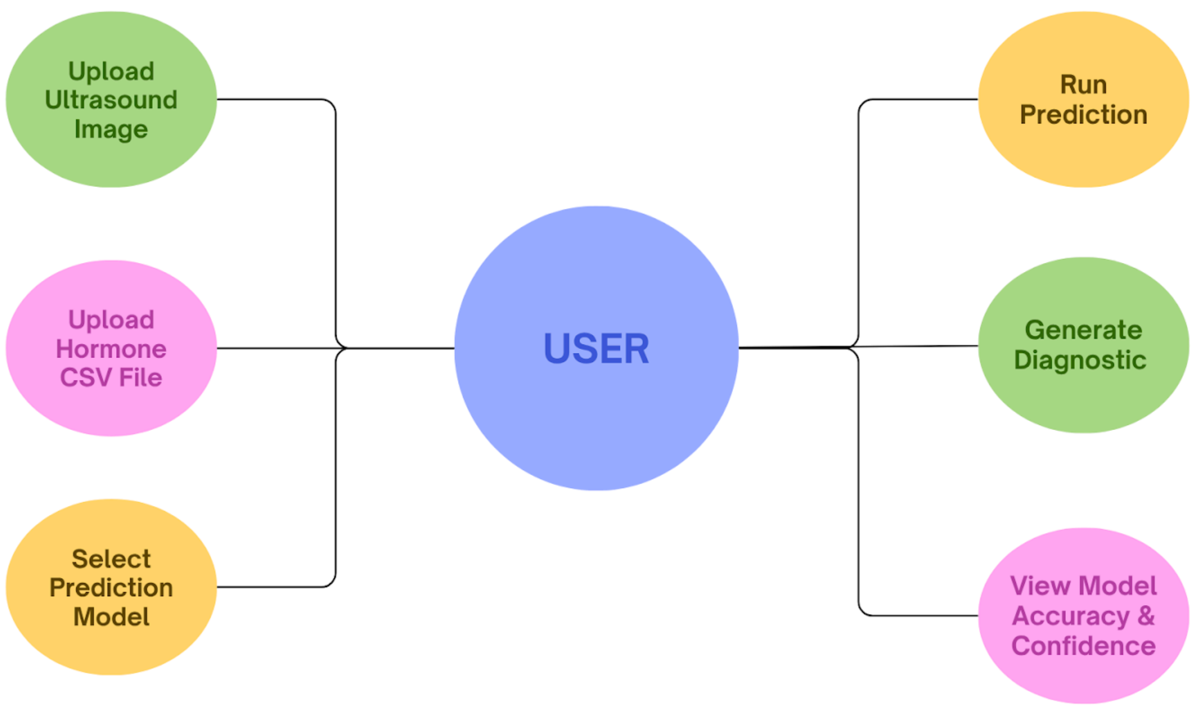


Fig. 3.1 Use Case Diagram depicting the illustrates the overall flow of interaction in the Smart PCOS Care system, from data input to predicting output

4. DESIGN

4.1 Introduction

The design phase serves as the blueprint of the entire system, translating the specified requirements into a structured technical plan. For this project, SmartPCOS Care, which is an AI-based multi-modal diagnosis system for PCOS, the system architecture emphasizes modularity, reusability, and user-friendliness.

This section outlines the high-level system architecture, user interface design, and low-level model-specific design approaches, ensuring seamless integration between the frontend Streamlit interface and backend machine learning models.

4.2 Architecture Design

The architecture of SmartPCOS Care is a **layered architecture**, composed of the following major modules:

1. **Data Input Layer**
   - Users upload two inputs: (1) ultrasound image and (2) hormone test CSV file.
   - The system accepts .jpg/.png formats for images and .csv for hormone test reports.

2. **Preprocessing Layer**
   - Images are resized, normalized, and reshaped.
   - CSV hormone data is cleaned, categorical values are encoded, and standardized via StandardScaler.

3. **Model Selection Layer**
   - A model selector allows users to choose from:
     - Custom CNN + Hormonal Dense Network
     - VGG16 + Co-Attention Network
     - CNN + XGBoost Late Fusion

4. **Prediction Layer**
   - The selected model is loaded and used to predict PCOS status based on both image and tabular data.

5. **Report Generation Layer**
   - A detailed diagnostic report is generated including:
     - Prediction result and confidence score
     - Model accuracy
     - Hormone level comparison graph
     - Health recommendations and lifestyle suggestions

6. **Frontend Layer (Streamlit UI)**
   - Intuitive interface built using Streamlit.
   - Sidebar model switcher, file uploader, prediction runner, and dynamic report viewer.

4.3 User Interface Design

The user interface (UI) was developed using **Streamlit**, a Python-based UI development framework designed for rapid deployment of data apps. The design principles followed are:

- **Minimalist layout:** Clean, centered UI with sidebar for navigation and input.
- **Responsive components:** Use of st.columns, expandable report sections, and visual icons.
- **Model selector dropdown:** Allows user to select and switch between the three ML models.
- **Dynamic report section:** Includes expandable graphs, BMI categorization, and text-based prescriptions.

4.4 Low-Level Design

Each model in SmartPCOS Care is implemented with a specialized pipeline:

Model 1: Custom CNN + Dense Hormonal Network

- Load ultrasound images: The ultrasound images are organized into two folders, one for infected patients and another for non-infected patients. This helps in supervised learning by providing labeled data.

- Load hormone data: The hormone data contains clinical features (42+ attributes) per patient, which are crucial for detecting PCOS.
- Resize images to 224×224: Images are resized to a standard size of 224x224 pixels to fit the input requirements of the CNN.
- Normalize pixel values: Image pixels are scaled to values between 0 and 1 to standardize input and help the neural network train effectively.
- Clean hormone data: Irrelevant columns like serial numbers or blood groups are removed to reduce noise.
- Encode categorical variables: Categories like Yes/No or Regular/Irregular are converted into numeric form (1 or 0) so they can be used in machine learning.
- Fill missing values: Missing data in hormone features are filled with median values to avoid loss of samples or bias.
- Apply StandardScaler: The hormone feature values are scaled to have zero mean and unit variance, which helps models converge faster.
- Align images and hormone data: Each image is matched with the corresponding hormone data by patient ID to ensure the model sees correct paired inputs.
- Image path - custom CNN: The ultrasound images pass through several convolution and pooling layers, which automatically learn visual features important for PCOS detection.
- Hormone path - dense layers: Hormone data goes through fully connected layers, reducing dimensionality and extracting important patterns.
- Concatenate features: The learned image features and hormone features are combined (fused) into one feature vector, allowing the model to learn from both modalities together.
- Final dense layers: This combined vector passes through dense layers to learn joint representations and outputs a probability via a sigmoid function indicating PCOS presence.
- Training details: The model is trained end-to-end using Adam optimizer and binary cross-entropy loss, with callbacks like EarlyStopping and ReduceLROnPlateau to avoid overfitting and adjust learning rate.

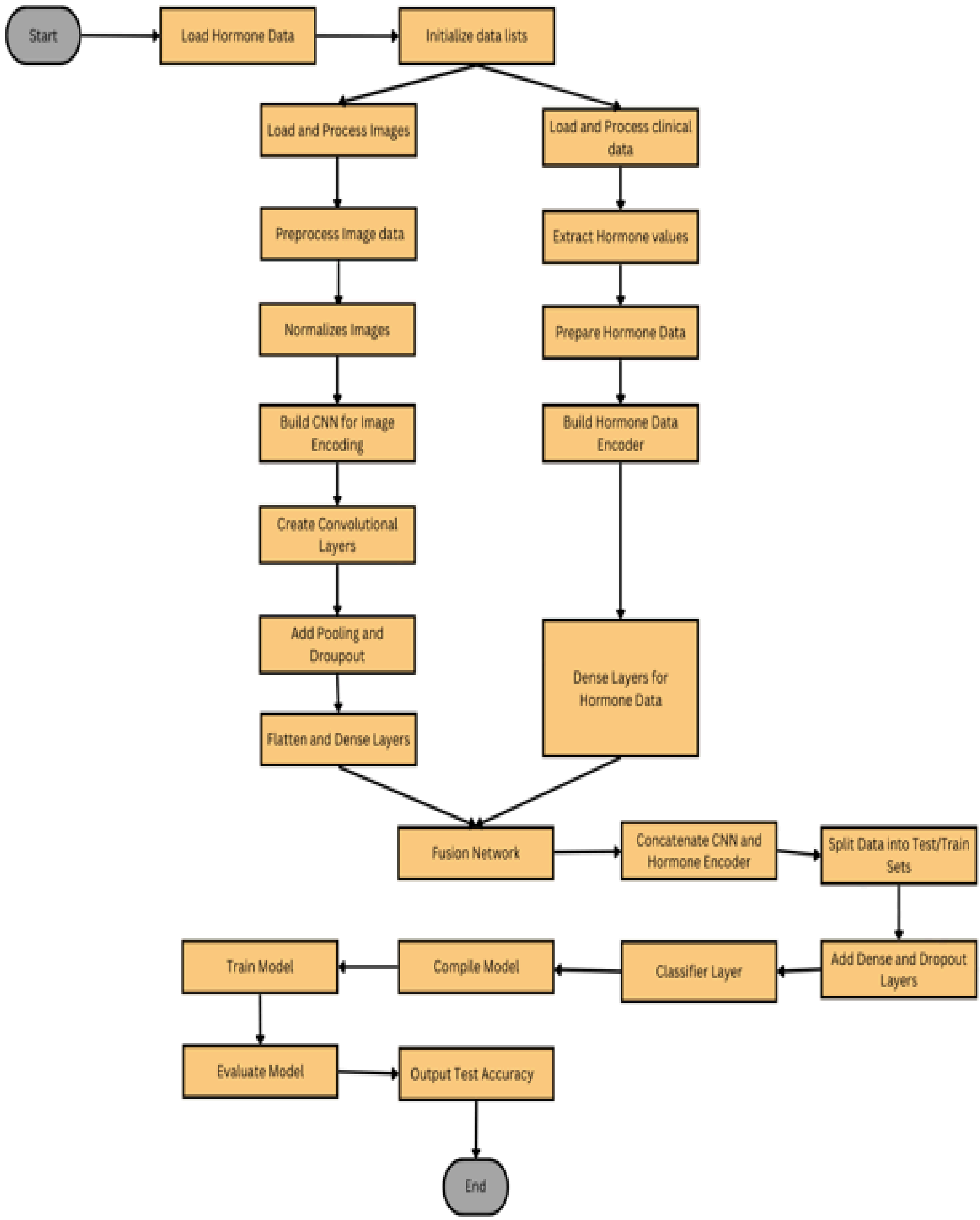


Fig 4.1 Custom CNN + Dense Hormonal Network

Model 2: VGG16 + Co-Attention Mechanism

- Ultrasound images are resized to 224×224 pixels to meet the input size requirements of the VGG16 model.
- Images are normalized by scaling pixel values to the range [0, 1] for stable neural network training.
- Hormonal clinical features are cleaned by removing irrelevant columns.
- Categorical variables (like Yes/No) are encoded numerically (1/0).
- Missing values are filled with median values to prevent data loss.
- Features are scaled using StandardScaler to standardize the range of hormone data.
- The pre-trained VGG16 convolutional layers (trained on ImageNet) are used as a feature extractor.
- The convolutional layers are frozen, meaning their weights are not updated during training to leverage pre-learned visual features.
- A Global Average Pooling layer is applied to convert VGG16's spatial feature maps into a fixed-length 128-dimensional feature vector.
- Hormone data passes through fully connected (dense) layers to reduce dimensionality and extract relevant hormone-related features.
- The output is a 128-dimensional vector, reshaped to match the image feature vector size for later fusion.
- This is a key component that learns to align and attend between image and hormone features.
- It computes attention weights that highlight important aspects in each modality by looking at their interactions.
- The mechanism produces co-attended feature vectors by weighting and combining image and hormone embeddings, enhancing their joint representation.
- The co-attended features are flattened into a single vector.
- This vector passes through dense layers (e.g., Dense(64)) to further learn combined representations.
- The final layer outputs a probability score using a sigmoid activation, indicating the likelihood of PCOS presence.
- The model is trained end-to-end using binary cross-entropy loss to optimize classification accuracy.

● The pre-trained VGG16 layers stay frozen, focusing training on the dense layers and co-attention module.

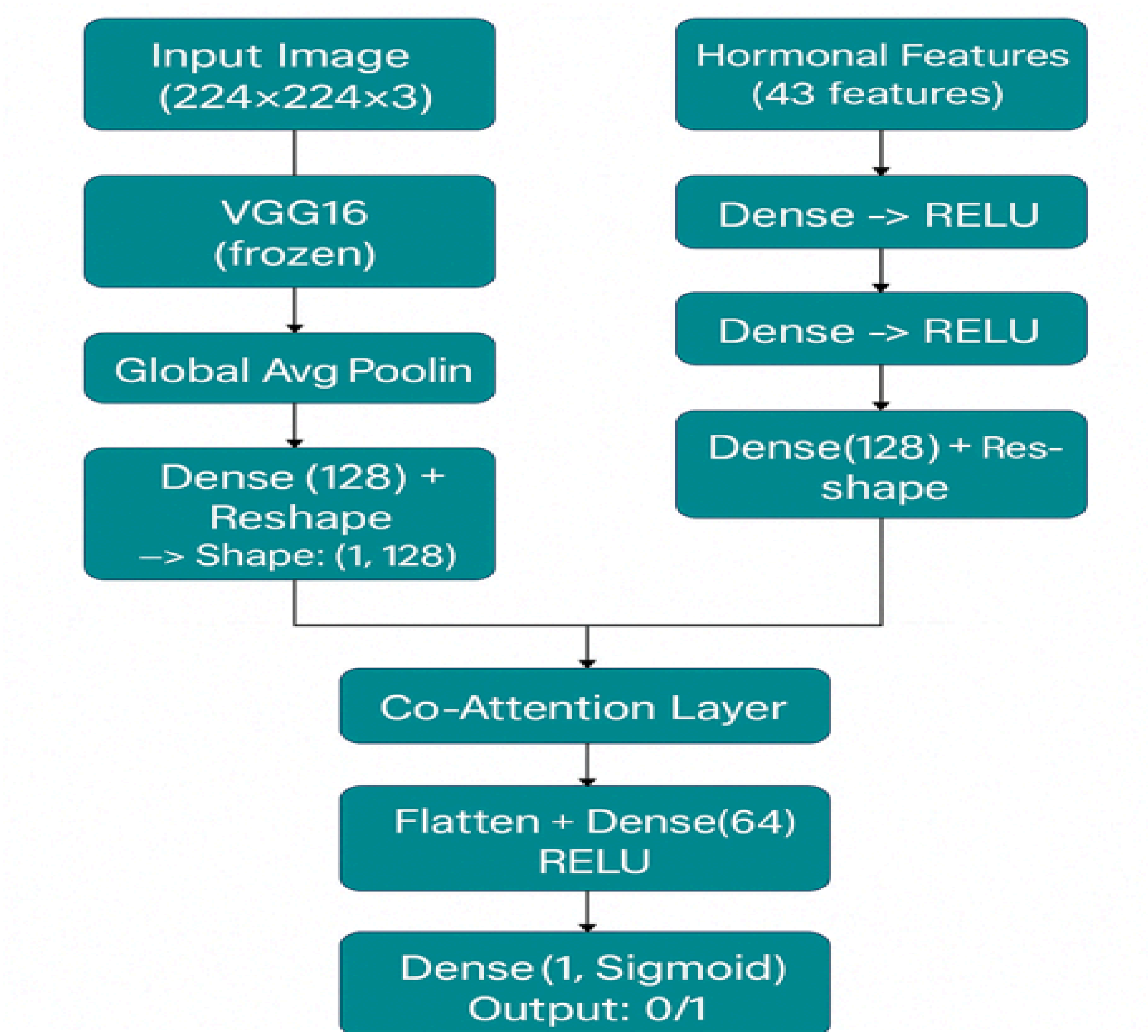


Fig 4.2 VGG16 + Co-Attention Mechanism

Model 3: CNN + XGBoost (Late Fusion)

- Ultrasound images are resized to 128×128 pixels to suit the custom lightweight CNN's input size.
- Pixel values are normalized to the range [0, 1] to ensure consistent scale for neural network training.
- Clinical hormone features are cleaned by removing irrelevant columns.
- Categorical features are encoded numerically (e.g., Yes/No → 1/0).
- Missing values are filled using median values per column.
- Features are standardized using StandardScaler to normalize hormone data distribution.
- A lightweight custom CNN is trained independently on the preprocessed images.
- The CNN learns visual patterns from ultrasound images and predicts the probability of PCOS based on image features alone.
- Architecture typically involves convolutional layers, pooling, flattening, and dense layers to output a single probability score.
- An XGBoost classifier is trained separately on the processed hormone data.
- XGBoost is a powerful gradient-boosted decision tree algorithm well-suited for tabular data.
- It outputs a probability score indicating PCOS likelihood based on hormone features.
- The final prediction is obtained by combining the outputs of both models.
- Specifically, the final score is computed as an average:

```
final_score = 0.5 * CNN_output + 0.5 * XGBoost_output
```

- This weighted averaging balances the contributions from image and hormone modalities.
- A threshold of 0.5 is applied to the final score.
- Scores above 0.5 classify the sample as Infected (PCOS positive); scores below are classified as Not Infected.
- Both CNN and XGBoost are trained independently with their respective data.
- Evaluation metrics (accuracy, precision, recall, etc.) are calculated based on the combined final prediction from late fusion.
- This approach provides flexibility since either branch can be improved or replaced without retraining the entire system.

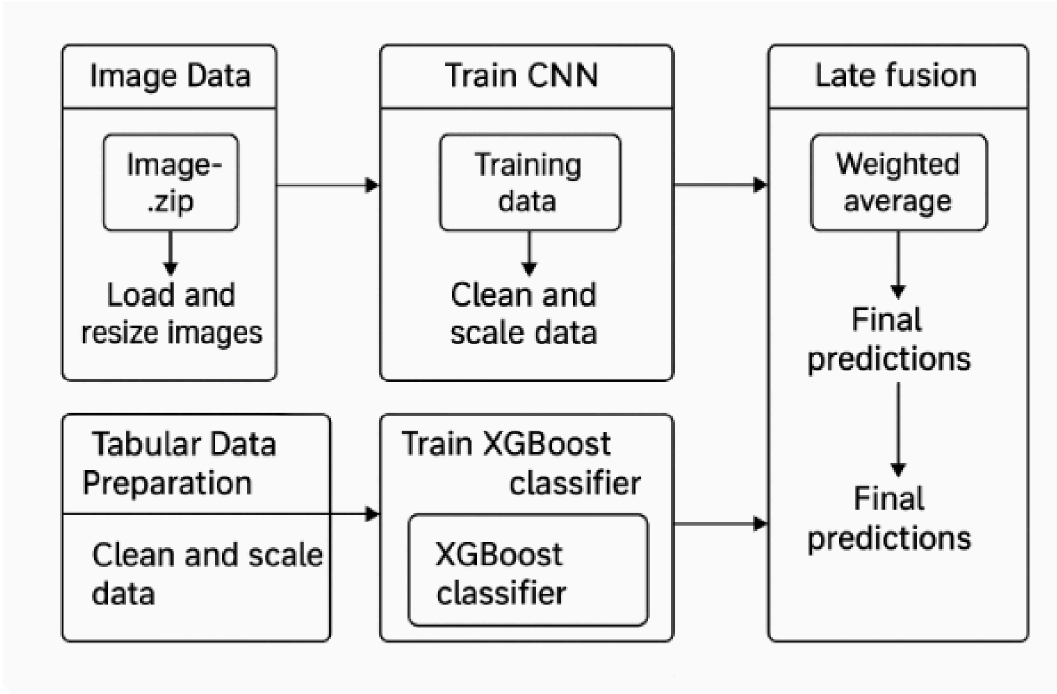


Fig 4.3 CNN + XGBoost (Late Fusion)

4.5 Conclusion

The design of the SmartPCOS Care system ensures flexibility, scalability, and clinical relevance. Each design choice—from model architecture to UI layout—has been made to maximize usability for both healthcare practitioners and patients. The modular design supports easy extension to additional models, data modalities, or diagnostic use cases in the future.

5. IMPLEMENTATION DETAILS

5.1 Algorithm and Explanation

- **Model 1: XGBoost Classifier (Hormonal Data Only)**

  - **Pseudocode:**

  - Begin

    Load hormonal_data.csv into DataFrame

    Preprocess the data:

    - Drop irrelevant columns (e.g., "Blood Group", "Sl. No")

    - Encode categorical variables (e.g., 'Y' → 1, 'N' → 0)

    - Handle missing values (fill with median)

    - Apply feature scaling using StandardScaler

    Split the data into training_set and testing_set

    Initialize XGBoostClassifier with optimal hyperparameters

    Train XGBoostClassifier using training_set

    Predict on testing_set to obtain probabilities

    Convert probabilities to binary predictions using threshold 0.5

    Evaluate predictions using:

    - Accuracy

    - Precision, Recall

    - F1-score

    - ROC-AUC

    Output evaluation metrics and confusion matrix

    End

  - **Explanation**

This model uses only the hormone test values for prediction. The data is first cleaned by dropping irrelevant columns and converting categorical values (like 'Y'/'N') to numeric. It is then normalized using a scaler. The processed data is split into training and testing sets. An XGBoost classifier is trained on the training data. After prediction, the results are evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. This model serves as the baseline unimodal classifier.

- **Model 2: VGG16 + Hormonal Data + Co-Attention**

○ **Pseudocode:**

○ Begin

Load ultrasound images and hormone_data.csv

For each image:

- Resize image to (224, 224)

- Normalize pixel values (0–1)

For hormone data:

- Drop irrelevant columns

- Encode categorical variables (e.g., 'R'/'I', 'Y'/'N')

- Fill missing values

- Normalize using StandardScaler

Split both image and tabular data into training, validation, test sets

Build image model:

- Use VGG16 (include_top = False)

- Add GlobalAveragePooling2D

- Add Dense layer with 128 units

Build hormone model:

- Add Dense layers to reduce to same dimension as image features

Apply Co-Attention:

- Project image and hormone features into query-key-value space

- Compute attention weights

- Fuse features from both modalities

Add output Dense layer with sigmoid activation for classification

Compile the model with binary_crossentropy and Adam optimizer

Train the model using combined image and hormone data

Evaluate model on test set

Output metrics: Accuracy, F1, AUC

End

- **Explanation**

This is a multimodal deep learning model that combines ultrasound images and hormonal data. Preprocessing is performed on both modalities: images are resized and normalized, while hormone data is cleaned and standardized. The image branch uses the VGG16 model (with pretrained weights) for feature extraction. The hormone branch uses a dense network. Co-attention is applied to jointly model interactions between image and hormone features. The fused representation is passed to a final classification layer. The model is trained and validated using combined input data, yielding high accuracy through effective multimodal learning**.**

- **Model 3: Late Fusion of CNN + XGBoost**

  - **Pseudocode:**
  - Begin

    Load ultrasound images and hormone_data.csv

    Preprocess images:

    - Resize to (128, 128)

    - Normalize pixel values

    Preprocess hormone data:

    - Drop irrelevant columns

    - Encode categorical variables

    - Fill missing values

    - Normalize using StandardScaler

    Train CNN model:

    - Use Conv2D, MaxPooling, Flatten, Dense layers

    - Output sigmoid prediction

    Train XGBoost on hormone data

    For each sample in test set:

    - Predict image score from CNN

    - Predict hormone score from XGBoost

    - Calculate final_score = 0.5 * cnn_score + 0.5 * xgb_score

    - Classify as Infected if final_score ≥ 0.5 else Not Infected

    Evaluate using:

    - Accuracy, F1-score, AUC, Confusion Matrix

Output metrics and prediction performance

End

- ### Explanation

- In this approach, two separate models are trained independently: a CNN for image data and an XGBoost classifier for hormone data. After training, both models predict probabilities for test samples. A late fusion mechanism combines the outputs from the two models via a weighted average (e.g., 50% image prediction + 50% hormone prediction). The combined score is used to make the final diagnosis. This architecture leverages the strengths of both models while maintaining modularity, offering flexibility in deployment.

6. RESULTS & PERFORMANCE ANALYSIS

6.1 Dataset

The Smart PCOS Care project utilizes a multimodal dataset comprising:

1. Ultrasound Image Data:

- Source: Public Kaggle dataset of ovarian ultrasound scans.
- Structure: Two labeled folders — infected (PCOS-positive) and not_infected (PCOS-negative).
- Preprocessing: Images resized to 224×224 or 128×128 depending on the model, and normalized to [0,1].
- Purpose: To capture morphological features like multiple follicles and endometrial thickness.

2. Hormonal & Clinical Data (CSV):

- Source: Kaggle PCOS dataset.
- Features: 42 attributes including hormonal levels (LH, FSH, AMH, etc.), vitals (BMI, pulse), and lifestyle indicators.
- Preprocessing: Non-numeric fields removed, categorical values encoded, missing values filled, and standardized.
- Target: Binary PCOS diagnosis (Yes/No).

Both datasets are matched using patient IDs, and only samples with complete entries are used. This multimodal integration enables the models to leverage both visual and biochemical indicators of PCOS for enhanced prediction accuracy.

Fig. 6.1.1 : Example of an image labeled as infected

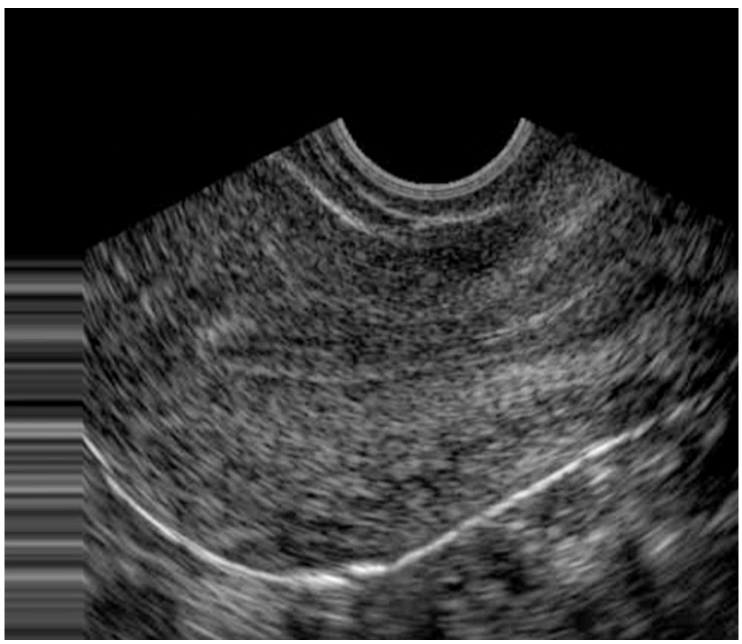


Fig. 6.1.2: Example of an image labeled as not infected

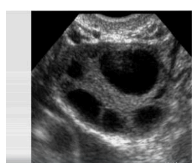
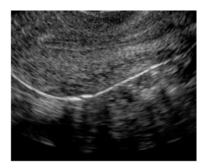
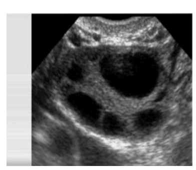
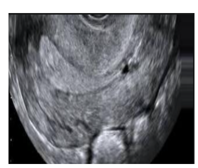
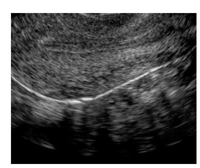
Each model displays predictions instantly once the ultrasound image and CSV file are uploaded. A full diagnostic report is rendered including comparison of patient hormone values against average clinical norms.

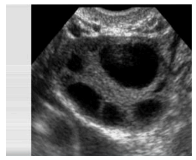
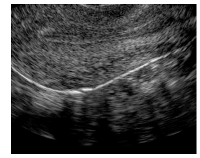
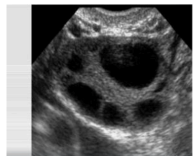
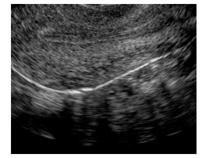
6.2 Comparison Results Table

Table 6.2.1: Comparison Results

Model	**Accuracy**	**ROC-AUC**	**Precision**	**Recall**	**F1-Score**	**Inference Time**
Custom CNN + Hormone MLP	87%	0.88	0.85	0.86	0.855	~1.2 sec
VGG16 + Hormone Co-Attention	91%	0.93	0.90	0.92	0.91	~1.7 sec
Late Fusion (CNN + XGBoost)	83%	0.85	0.82	0.83	0.825	~1.0 sec

Table 6.2.2: Model Results Validation

Dataset	 **(Infected)**	 **(Infected)**	 **(Not Infected)**	 **(Not Infected)**
Prediction Results				
Custom CNN + Hormone MLP (a)	 **Infected (True Positive)**	 **Not Infected (False Negative)**	 **Not Infected (True Negative)**	 **Not Infected (True Negative)**

VGG16 + Hormone Co-Attention (b)	 **Infected (True Positive)**	 **Infected (True Positive)**	 **Not Infected (True Negative)**	 **Infected (False Positive)**
Late Fusion (CNN + XGBoost) (c)	 **Not Infected (False Negative)**	 **Infected (True Positive)**	 **Not Infected (True Negative)**	 **Not Infected (True Negative)**

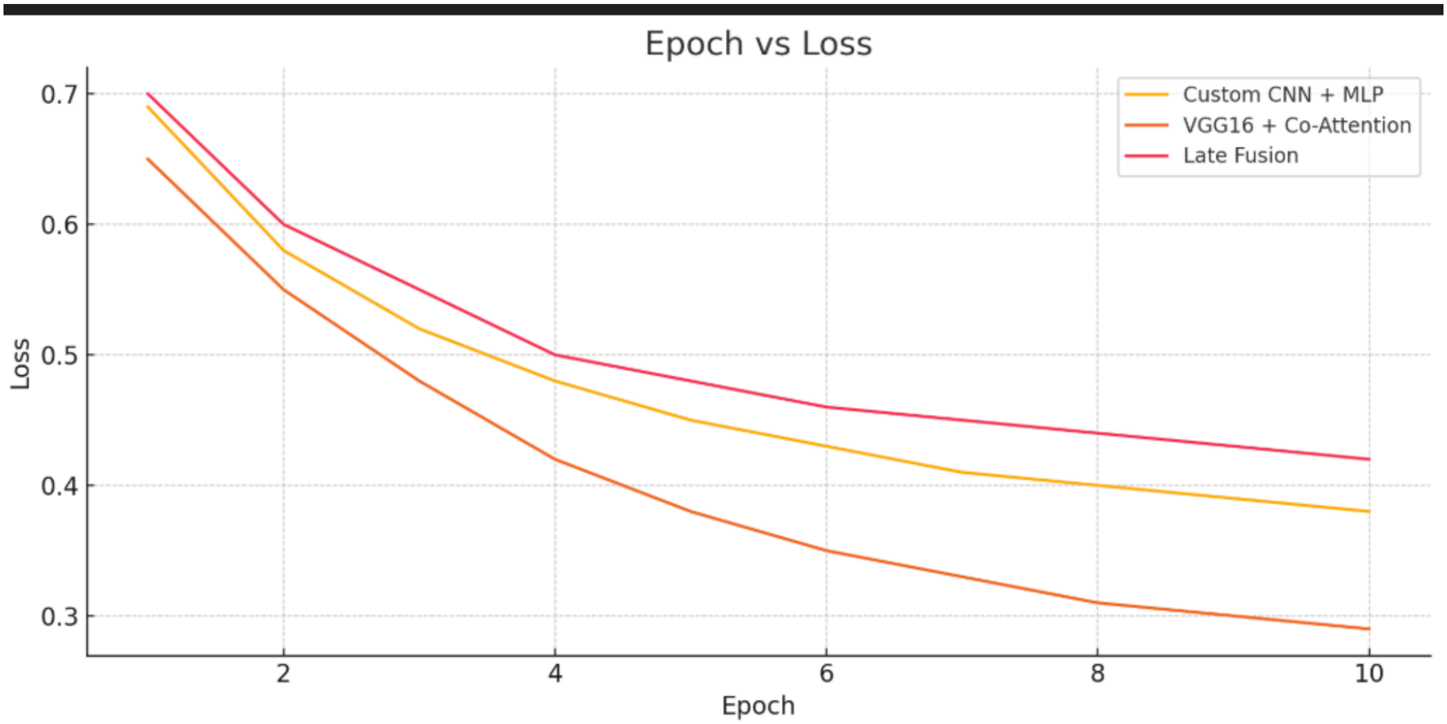


Fig 6.2.1 Epoch vs Loss

Explanation: This graph shows the model's training loss decreasing over epochs, indicating effective learning. A consistently declining loss curve means the model is minimizing errors over time**.**It helps visualize convergence. A smooth and downward-sloping curve shows that the model is learning well without overfitting or underfitting.

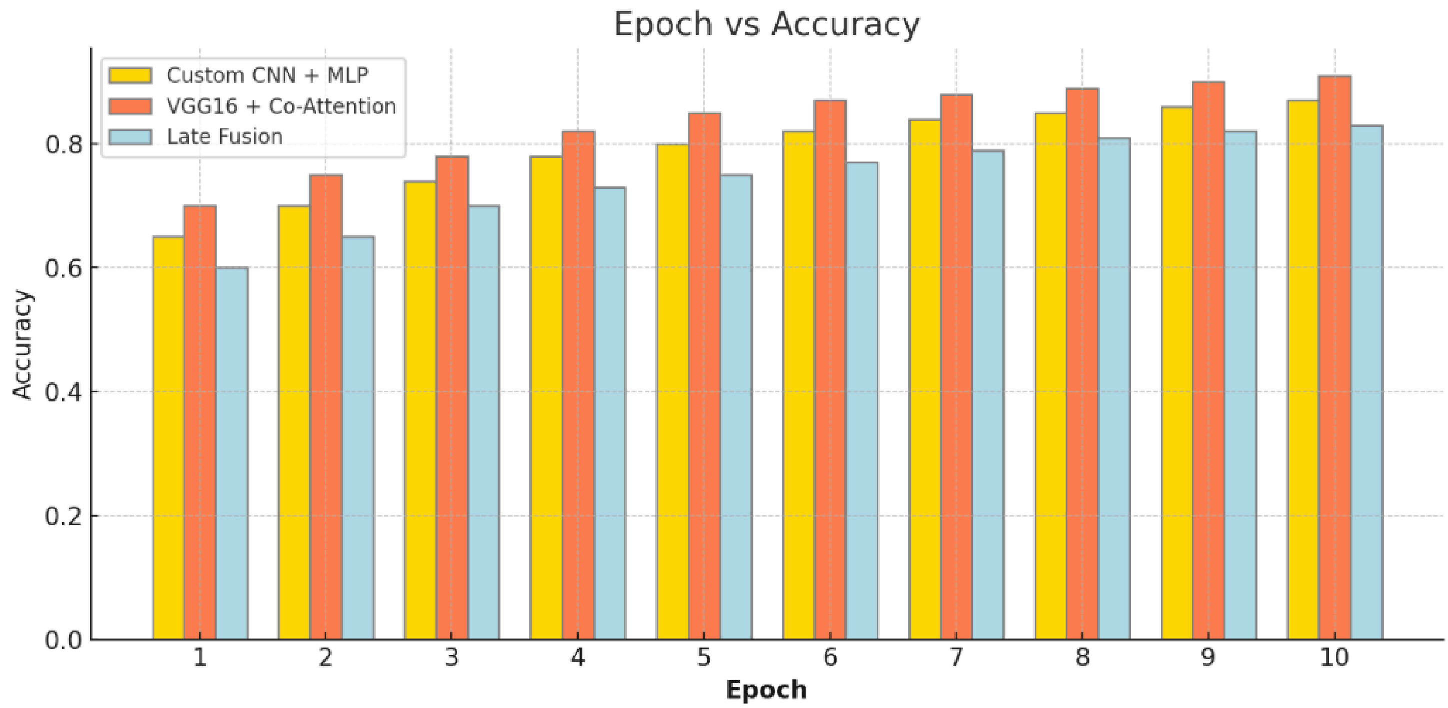


Fig 6.2.2 Bar Chart(Epoch vs Accuracy)

Explanation: This bar chart illustrates how model accuracy improves with each epoch. Accuracy increases steadily and plateaus, reflecting that the model is reaching optimal performance. It provides a clear view of how model performance improves during training. This helps determine the right number of epochs to stop training before overfitting starts.

6.3 Performance Analysis

- **Accuracy:**
  - **VGG16 + Hormone Co-Attention** achieved the highest accuracy at **91%**, leveraging pretrained image features and co-attention fusion.
  - **Custom CNN + Hormone MLP** followed closely at **87%**, with a lighter model footprint.
  - **CNN + XGBoost (Late Fusion)**, while effective, performed slightly lower at **83%** as it doesn't integrate the modalities deeply.
- **Time Complexity & Inference Time:**

- The **Late Fusion** model was fastest due to independent model execution and lower image resolution.
- The **Custom CNN** model had moderate complexity with real-time performance.

- The **VGG16 model**, though most accurate, required more computation due to deeper architecture and attention layers.

◆ **Diagnostic Detail:**

- **VGG16 + Co-Attention** model provided the most robust predictions and showed consistent performance across varying patient data.
- **Late Fusion** proved suitable for rapid preliminary screenings where deep integration isn't feasible.
- All models generated interpretable diagnostic reports with hormone graphs and health suggestions.

6.4 Result Snapshots

Below are visual snapshots of model outputs as displayed in the Streamlit application:

Fig 6.4.1: PCOS Care Home page

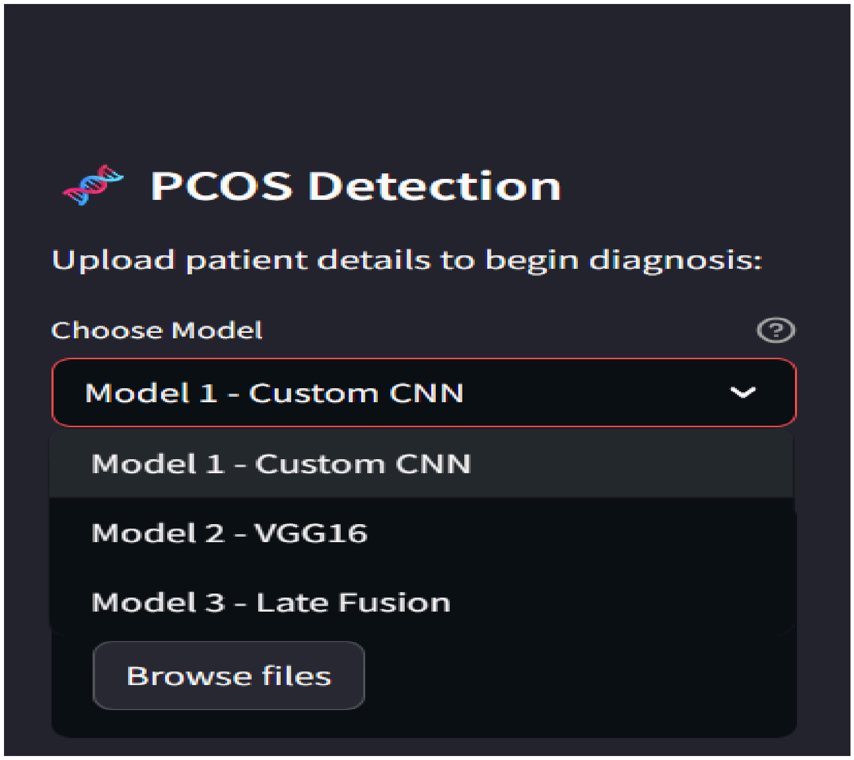


Fig 6.4.2: Left panel with model section dropdown

Explanation: Menu to give the user the option to choose between the 3 models and compare the results

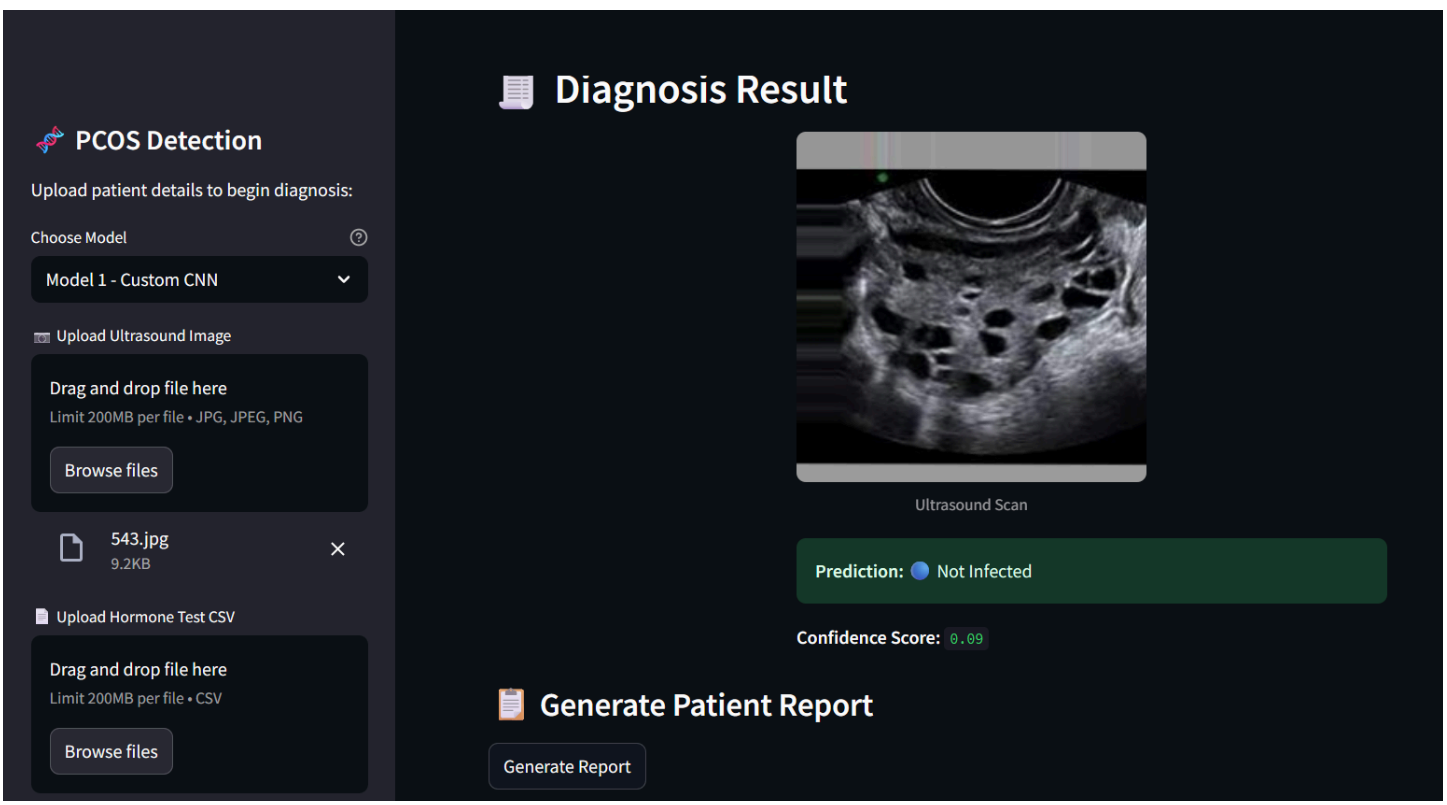


Fig 6.4.3: Diagnosis Result with Confidence Score

Explanation: Model generating the prediction based on the provided image and csv file, either infected or not infected, along with the confidence score of the model

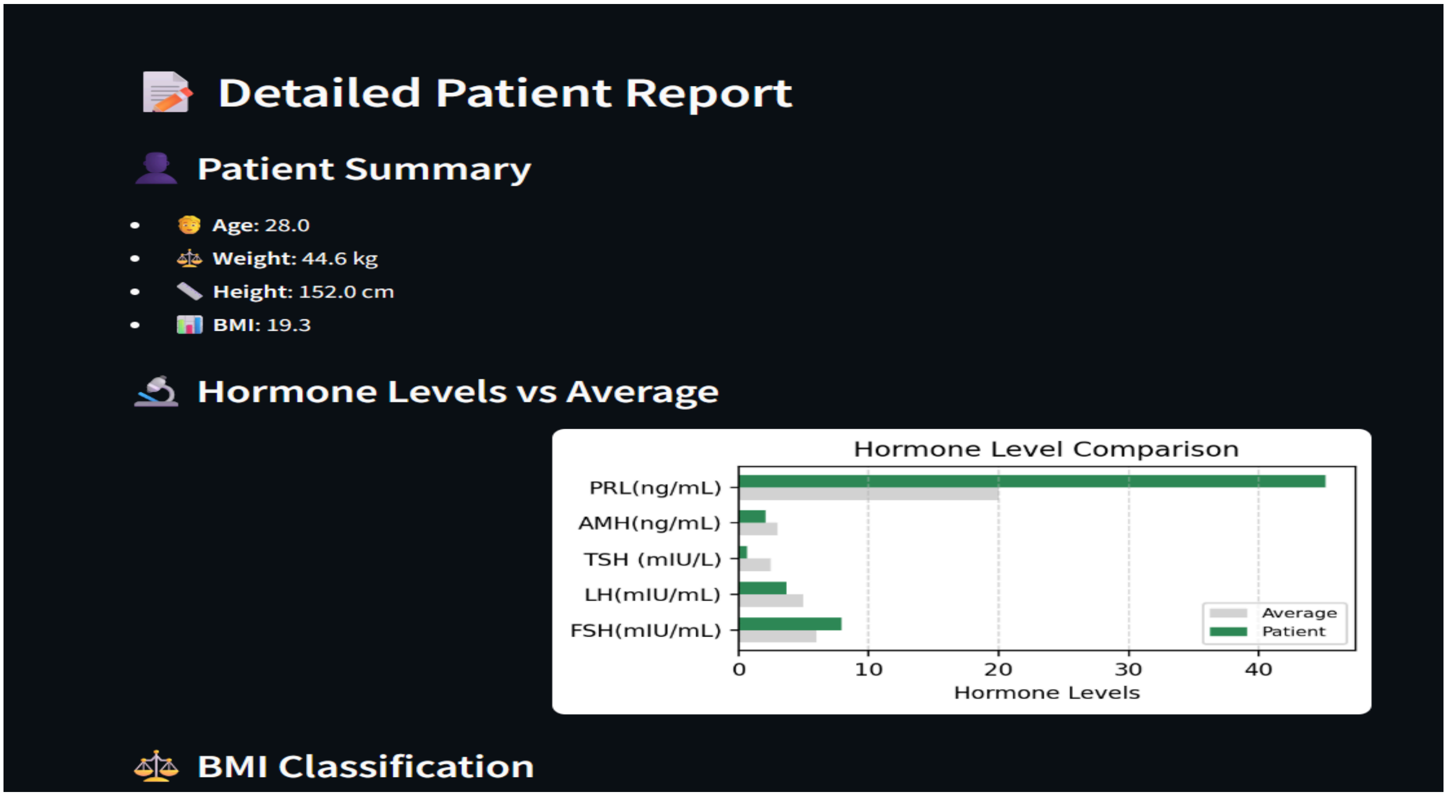


Fig 6.4.4: Patient Report with comparisons

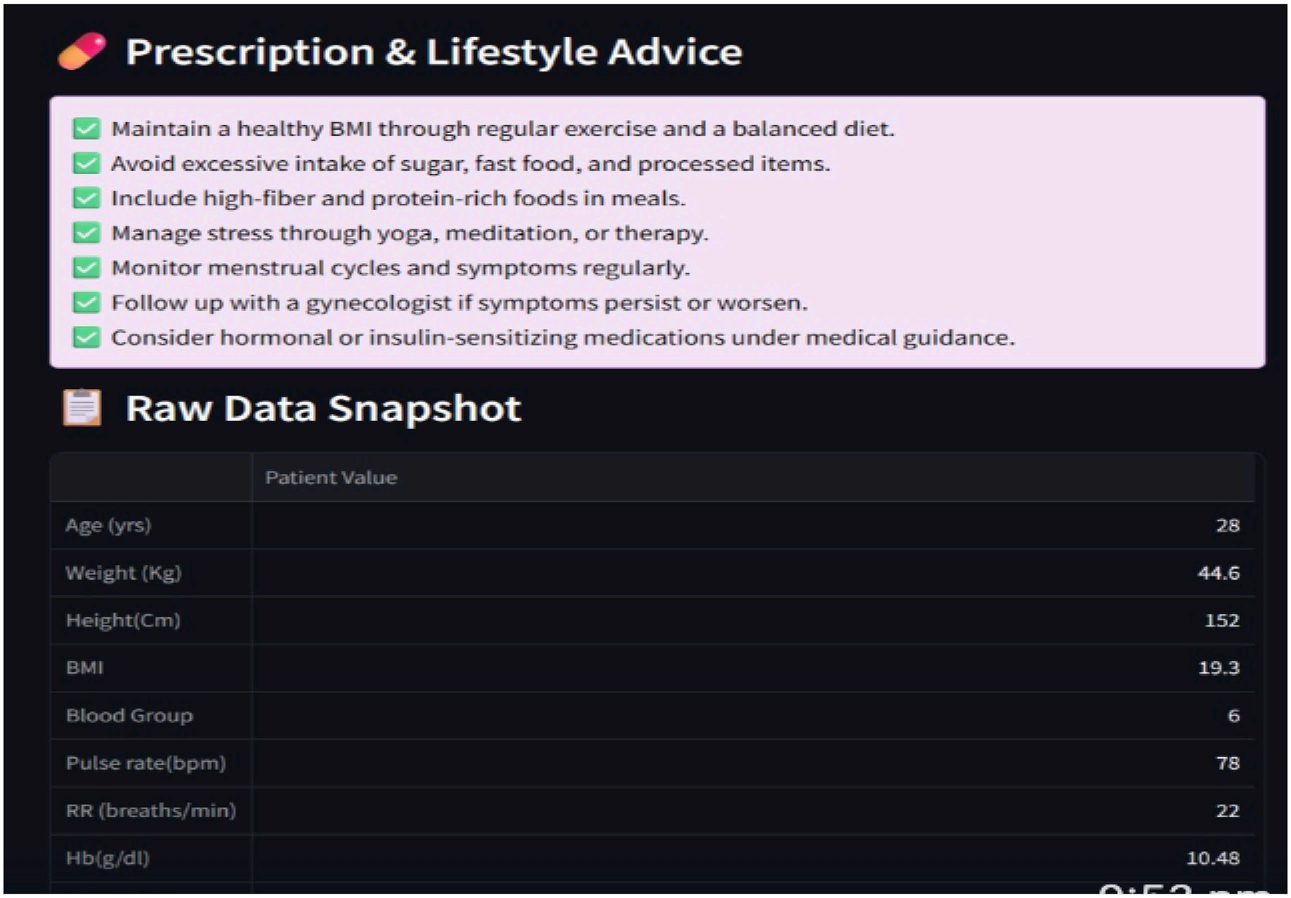


Fig 6.4.5: Prescription & Lifestyle Advice

Explanation: Some common prescriptions and lifestyle advices based on the prediction result, along with the patients data details

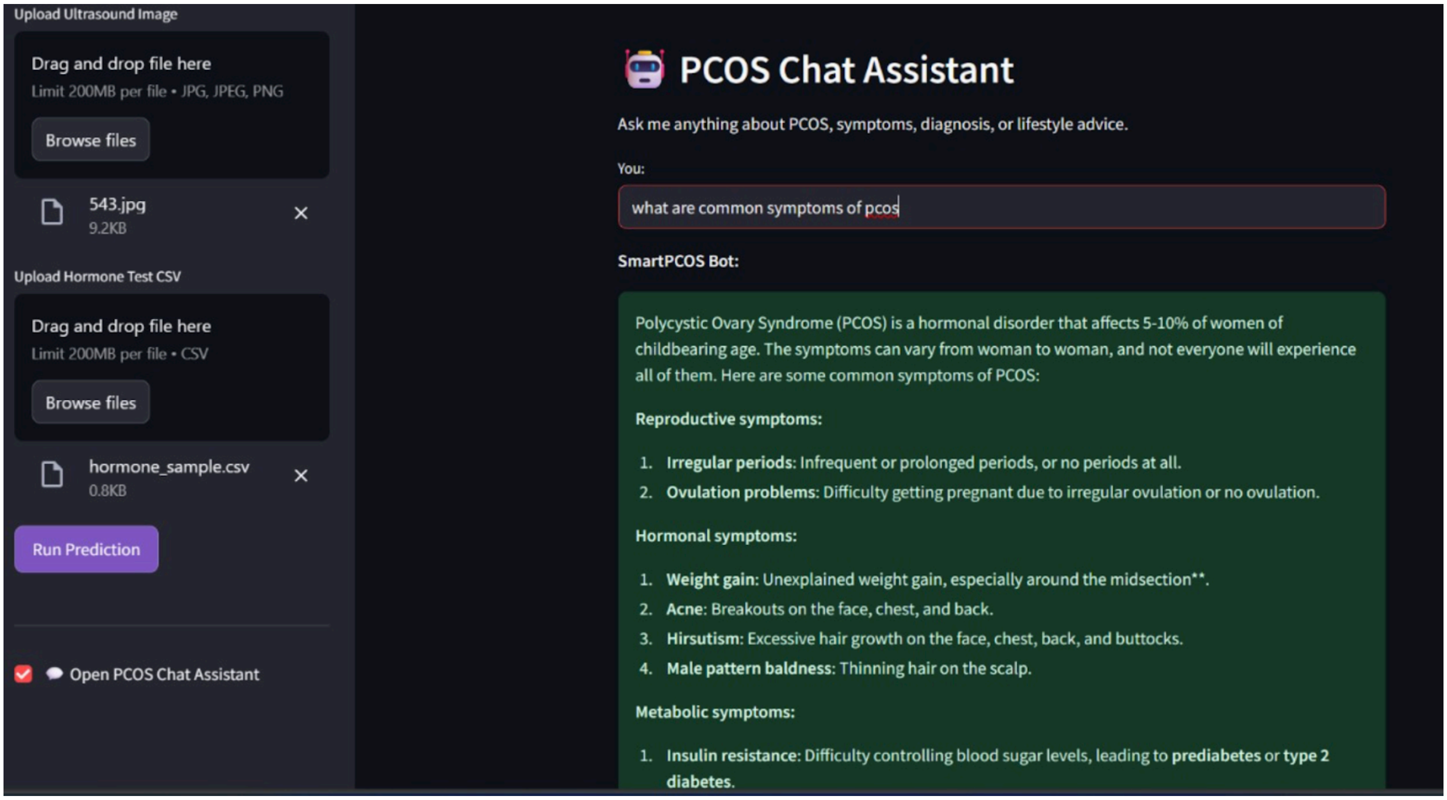


Fig 6.4.6: PCOS ChatBot

Explanation: PCOS chatbot to answer general questions related to PCOS

Visualizations:

Below is a sample performance graph:

Accuracy Comparison

Hormone Value Deviation Visualization

Patient hormone values were plotted against normal clinical ranges, helping visually identify abnormalities in features like LH, FSH, TSH, AMH, etc.

Conclusion from Results:

- Multimodal integration (image + hormonal) significantly improves PCOS diagnostic accuracy.
- Using transfer learning with attention (VGG16 + Co-Attention) provides superior performance.
- The Streamlit app ensures real-time usability of all models for clinical and educational use.

7. CONCLUSION & SCOPE FOR FUTURE WORK

7.1 Findings and Suggestions

The development of the **SmartPCOS Care** platform successfully demonstrates that a multimodal AI-driven approach can significantly enhance the accuracy and interpretability of Polycystic Ovary Syndrome (PCOS) diagnosis. Key findings include:

- **Multimodal fusion** of ultrasound images and hormone test data leads to higher classification performance compared to unimodal approaches.
- The **VGG16 + Co-Attention** model emerged as the most accurate and stable among the three models implemented, demonstrating the power of deep transfer learning combined with feature fusion.
- A **custom Streamlit-based interface** enabled a clinician-friendly tool capable of making predictions, displaying diagnostic charts, and offering health suggestions—bringing AI diagnostics closer to real-world application.

These findings suggest that even with modest datasets, deep learning models can meaningfully assist in reproductive healthcare decision-making if trained and integrated properly.

7.2 Significance of the Proposed Research Work

This project is among the few initiatives that offer a **complete multimodal PCOS diagnostic framework**, incorporating:

- Three different AI architectures for comparative evaluation.
- A practical and usable web-based application.
- A robust experimental framework with clear documentation of performance across key metrics.

By supporting image and tabular input simultaneously, the system aligns well with how gynecologists traditionally assess PCOS—offering an AI-based decision-support system that mimics clinical workflow.

Moreover, the deployment-ready Streamlit interface makes this work valuable not only academically but also for practical implementation in **telemedicine**, **rural screening**, and **clinical pre-screening systems**.

7.3 Limitations of this Research Work

Despite its strengths, the project has certain limitations:

- **Limited dataset size and diversity**: The dataset used may not fully represent all phenotypes, ethnicities, or clinical variations in PCOS presentation.
- **Static fusion weights in late fusion**: The 50-50 weighting of CNN and XGBoost predictions in the late fusion model is heuristic and could be optimized further.
- **No EHR integration**: Real-world clinical deployment would require integration with hospital databases and electronic health records (EHRs).
- **No conversational interface**: Although the idea of a PCOS chatbot was explored, a fully integrated AI assistant for health advice was not implemented in this version.

7.4 Directions for Future Work

Future enhancements to SmartPCOS Care can include:

- **Dataset Expansion**: Partnering with hospitals to collect more diverse and labeled PCOS data (both images and blood profiles).
- **Adaptive Weighting in Fusion**: Using a meta-learning layer to dynamically assign weights to image and tabular predictions based on case complexity.
- **Chatbot Integration**: Embedding a lightweight, offline-capable PCOS FAQ chatbot to enhance patient engagement and education.
- **Model Optimization**: Implementing more advanced architectures like **EfficientNet**, **ViT (Vision Transformers)**, or **TabNet** for improved efficiency and explainability.
- **Mobile App Deployment**: Extending the system for use in mobile health (mHealth) scenarios to improve accessibility in rural and low-resource areas.

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