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OvaSense: An Intelligent Deep Learning-Based System for Ovarian Cyst Detection Using Ultrasound Images

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Abstract

Ovarian cysts are among the most common gynecological disorders affecting women across various age groups and may lead to serious health complications if not detected and classified at an early stage. Accurate identification of cyst types such as simple, complex, and polycystic ovarian conditions plays a critical role in determining appropriate treatment strategies and improving patient outcomes. However, conventional diagnostic approaches primarily depend on manual interpretation of ultrasound images by radiologists, which can be time-consuming, subjective, and prone to inter-observer variability. To address these challenges, this research proposes OvaSense, an intelligent deep learning-based diagnostic framework designed for automated detection and classification of ovarian cysts using ultrasound imaging.

Furthermore, the OvaSense system is designed with scalability and usability in mind, allowing integration into clinical workflows and assisting healthcare professionals in early diagnosis and treatment planning. The results highlight the effectiveness of combining object detection and deep learning-based classification techniques for medical image analysis, making the proposed framework a promising decision-support tool for modern intelligent healthcare systems.

Keywords: Ovarian Cyst Detection, Deep Learning, YOLOv8, CNN, VGG16, Ultrasound Imaging, Medical Image Analysis, Artificial Intelligence in Healthcare.

I. Introduction

Ovarian cysts are fluid-filled sacs that develop within or on the surface of the ovaries and are among the most frequently occurring gynecological conditions affecting women, particularly during their reproductive years. Although many ovarian cysts are benign and resolve naturally without medical intervention, certain types such as complex cysts and polycystic ovarian conditions may lead to severe complications including infertility, hormonal imbalance, pelvic pain, and in rare cases, ovarian cancer. Therefore, early detection and accurate classification of ovarian cyst types—such as simple cysts, complex cysts, and polycystic ovarian syndrome (PCOS)—are essential for effective diagnosis, treatment planning, and prevention of long-term health risks.

Ultrasound imaging is one of the most commonly used diagnostic techniques for identifying ovarian abnormalities due to its non-invasive nature, affordability, safety, and wide availability in clinical settings. It provides real-time visualization of ovarian structures and plays a crucial role in routine gynecological examinations. However, the interpretation of ultrasound images is traditionally performed manually by radiologists and gynecologists, making the diagnostic process highly dependent on clinical expertise and experience. This manual analysis can sometimes result in variability between observers, delayed diagnosis, increased workload for healthcare professionals, and potential misclassification of cyst types, especially in complex imaging scenarios.

In recent years, the rapid advancement of Artificial Intelligence (AI), particularly deep learning techniques, has significantly transformed the field of medical image analysis. Deep learning models such as Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in automatically extracting meaningful features from medical images and performing classification tasks with high accuracy. Similarly, object detection algorithms such as YOLO (You Only Look Once) have enabled real-time localization of anatomical regions and abnormalities within medical images, making them highly suitable for clinical decision-support applications.

Motivated by these technological advancements, this research proposes OvaSense, an intelligent deep learning-based diagnostic system designed to automate the detection and classification of ovarian cysts using ultrasound images. The proposed system integrates the YOLOv8 object detection model for accurate localization of ovarian regions with a CNN-based classification framework utilizing the VGG16 architecture for identifying cyst types. By combining detection and classification techniques into a unified framework, the system aims to improve diagnostic accuracy, reduce dependency on manual interpretation, minimize human error, and provide real-time assistance to healthcare professionals.

The primary objective of this research is to develop an efficient and reliable automated diagnostic support system that enhances clinical workflow and assists radiologists in making faster and more consistent decisions. The proposed OvaSense framework contributes to the growing field of intelligent healthcare systems by demonstrating how deep learning techniques can be effectively applied to ultrasound-based ovarian cyst detection and classification, ultimately improving patient care and treatment outcomes.

II. Literature Review

In recent years, deep learning techniques have significantly transformed the field of medical image analysis by enabling automated detection, segmentation, and classification of various diseases. Among these techniques, Convolutional Neural Networks (CNNs) have been widely adopted due to their strong capability to automatically extract hierarchical features from medical images without requiring manual feature engineering. CNN-based architectures have demonstrated remarkable performance in detecting abnormalities in radiological images such as tumors, cysts, and lesions across different imaging modalities including ultrasound, MRI, and CT scans.

Pre-trained deep learning models such as VGG16, ResNet, and Inception have been extensively used in transfer learning applications for medical imaging tasks. Transfer learning allows models trained on large benchmark datasets to be adapted for domain-specific medical datasets, thereby improving classification accuracy even when limited training samples are available. Among these architectures, VGG16 has shown excellent performance due to its simple structure, deep feature extraction capability, and effectiveness in distinguishing subtle variations in medical image textures.

Object detection algorithms have also gained increasing attention in recent years for their ability to localize abnormalities within medical images. The YOLO (You Only Look Once) family of models is particularly popular for real-time object detection tasks because of its high detection speed and accuracy. Earlier versions such as YOLOv3 and YOLOv5 have been successfully applied in several healthcare applications including tumor localization, breast cancer detection, and organ segmentation. The latest version, YOLOv8, offers improved detection accuracy, faster inference speed, and better generalization performance, making it highly suitable for ultrasound-based diagnostic systems that require real-time processing capabilities.

Several researchers have applied deep learning approaches for detecting ovarian abnormalities and gynecological disorders using ultrasound imaging. Existing studies primarily focus on classification-based approaches using CNN architectures to differentiate between normal and abnormal ovarian conditions. Some research works have explored segmentation techniques to identify ovarian follicles in polycystic ovarian syndrome (PCOS) patients. However, many of these systems rely only on classification models without incorporating object detection mechanisms to precisely localize the region of interest within ultrasound images.

Furthermore, previous studies on ovarian cyst detection often suffer from limitations such as small dataset sizes, lack of real-time processing capability, limited model generalization across diverse imaging conditions, and insufficient integration of hybrid deep learning frameworks. In many cases, the absence of automated localization techniques increases the dependency on manual preprocessing steps performed by medical professionals, which reduces system efficiency and scalability in real clinical environments.

Recent advancements in hybrid deep learning architectures that combine object detection and classification models have demonstrated promising results in improving diagnostic accuracy and reducing computational complexity. Integrating detection models such as YOLO with classification networks such as VGG16 enables more precise localization of abnormal regions followed by accurate categorization of disease types. This combination enhances both the reliability and efficiency of automated diagnostic systems.

Despite these advancements, limited research has been conducted specifically on ovarian cyst classification using an integrated framework that supports both automated detection and classification with real-time performance. Therefore, this research proposes the OvaSense system, which combines YOLOv8 for region-of-interest detection with a CNN-based VGG16 classification model to develop a comprehensive and efficient diagnostic solution for ovarian cyst detection using ultrasound images. The proposed approach aims to address the limitations of existing methods by improving diagnostic accuracy, reducing manual intervention, and supporting real-time clinical decision-making.

III. Problem Formulation and Identified Research Gap

- Problem Formulation

The diagnosis of ovarian cysts primarily relies on the manual interpretation of ultrasound images performed by experienced radiologists and gynecologists. Although ultrasound imaging is widely used due to its safety, accessibility, and cost-effectiveness, the accuracy of diagnosis largely depends on the expertise and experience of medical professionals. This manual diagnostic process is often time-consuming and may lead to inconsistencies in interpretation, particularly when dealing with complex cyst structures or low-quality ultrasound images. In busy clinical environments, the increasing number of patient cases further adds to the workload of healthcare professionals, which can delay diagnosis and treatment planning.

Additionally, manual examination increases the possibility of human error and inter-observer variability, which may affect the reliability of classification results. The absence of intelligent automated systems capable of detecting and classifying ovarian cysts in real time further limits the efficiency of existing diagnostic workflows. Therefore, there is a strong need to develop an intelligent and automated diagnostic framework that can accurately detect and classify ovarian cysts from ultrasound images with minimal human intervention while supporting faster and more consistent clinical decision-making.

- Identified Research Gap

Based on the analysis of existing literature, several research gaps have been identified in the current approaches for ovarian cyst detection and classification using medical imaging techniques. Most existing systems rely primarily on manual interpretation or standalone classification models without incorporating automated object detection mechanisms for accurate localization of ovarian abnormalities. Furthermore, only limited research has explored the integration of object detection models such as YOLO with deep learning classification architectures like Convolutional Neural Networks (CNNs) for developing a hybrid diagnostic framework.

Another important limitation observed in previous studies is the lack of real-time diagnostic support systems that can assist healthcare professionals during clinical examinations. In addition, the availability of large and diverse annotated ultrasound datasets remains a challenge, which affects the generalization capability and robustness of deep learning models. Many existing solutions also lack user-friendly interfaces that can be easily adopted by non-technical medical staff in routine clinical practice.

To address these challenges, the proposed OvaSense system introduces a hybrid deep learning-based framework that integrates YOLOv8 for automated region-of-interest detection with a CNN-based VGG16 architecture for accurate classification of ovarian cyst types. The system is designed to improve diagnostic accuracy, reduce manual workload, support real-time decision-making, and provide an accessible interface suitable for practical deployment in healthcare environments.

IV. Research Objectives and Contributions

A. Research Objectives

The primary objective of this research is to design and develop an intelligent deep learning-based diagnostic system for the automated detection and classification of ovarian cysts using ultrasound images. The proposed framework aims to assist healthcare professionals in improving diagnostic accuracy while reducing reliance on manual interpretation, which is often time-consuming and subject to variability depending on clinical expertise.

Another key objective of this study is to implement a hybrid deep learning architecture that integrates advanced object detection and classification techniques within a unified framework. Specifically, the system utilizes the YOLOv8 model for accurate localization of ovarian regions from ultrasound images and a Convolutional Neural Network based on the VGG16 architecture for classification of different ovarian cyst types such as simple cysts, complex cysts, and polycystic ovarian conditions. This integration ensures efficient feature extraction and enhances the overall reliability of automated diagnosis.

In addition to improving detection accuracy, this research also aims to develop a system capable of supporting real-time clinical decision-making by reducing processing time and enabling faster prediction results. The automation of ovarian cyst detection can significantly reduce the workload of radiologists and gynecologists, particularly in high-volume healthcare environments where rapid diagnosis is essential for effective treatment planning.

Another important objective of the proposed research is to investigate the effectiveness of transfer learning techniques in improving classification performance when working with limited annotated medical imaging datasets. By leveraging pre-trained deep learning architectures such as VGG16, the study aims to enhance feature representation capability and improve model generalization across different ultrasound image conditions.

Furthermore, this research focuses on designing a scalable and user-friendly diagnostic support framework that can be integrated into existing hospital information systems and imaging workflows. The proposed system is intended to assist both technical and non-technical medical staff by providing an intuitive interface for uploading ultrasound images and obtaining classification results with minimal operational complexity.

Finally, the research also aims to evaluate the performance of the proposed deep learning framework using standard evaluation metrics such as accuracy, precision, recall, and F1-score to ensure reliability, robustness, and clinical applicability of the system in real-world healthcare environments.

B. Research Contributions

This research makes several important contributions to the field of intelligent medical image analysis and computer-aided diagnosis systems for gynecological healthcare applications.

The first major contribution of this work is the development of OvaSense, an intelligent deep learning-based diagnostic framework designed specifically for automated ovarian cyst detection and classification using ultrasound images. The proposed system provides an efficient alternative to traditional manual diagnostic methods by supporting faster and more consistent interpretation of medical images.

The second contribution of this research is the implementation of a hybrid deep learning architecture that integrates the YOLOv8 object detection model with a CNN-based VGG16 classification network. This combination enables precise localization of ovarian regions followed by accurate classification of cyst types, thereby improving overall system performance compared to standalone classification approaches.

Another significant contribution of this work is the incorporation of transfer learning techniques to enhance model training efficiency and improve classification accuracy, particularly when working with relatively limited medical imaging datasets. This approach reduces training complexity while maintaining high predictive performance.

The proposed system also contributes by enabling real-time analysis of ultrasound images, which supports faster clinical decision-making and improves diagnostic workflow efficiency in hospitals and diagnostic centers. The ability to automatically detect abnormalities within ultrasound images helps reduce diagnostic delays and assists healthcare professionals in providing timely treatment recommendations.

Furthermore, this research emphasizes the development of a scalable and user-friendly system architecture that can be easily extended for deployment in cloud-based healthcare platforms, telemedicine applications, and remote diagnostic environments. The framework can also be adapted in the future to support detection of other gynecological abnormalities using similar deep learning techniques.

Another important contribution of this study is the demonstration of how hybrid deep learning models combining object detection and classification techniques can be effectively applied to ultrasound-based medical imaging problems. This highlights the potential of artificial intelligence-driven diagnostic tools in improving healthcare service delivery and supporting clinical decision-support systems.

Overall, the proposed OvaSense framework represents a reliable and efficient intelligent healthcare solution that contributes toward advancing automated medical imaging technologies and improving patient care through early and accurate detection of ovarian cyst abnormalities.

V. Methodology

The proposed OvaSense system follows a structured deep learning-based workflow for automated detection and classification of ovarian cysts using ultrasound images. The methodology consists of several important stages, including dataset collection, preprocessing, region-of-interest detection, feature extraction, classification, model training, and performance evaluation. Each stage contributes to improving the overall efficiency and accuracy of the diagnostic framework.

A. Data Collection

The first stage of the proposed methodology involves the collection of ultrasound images of ovarian cysts from publicly available medical imaging datasets and clinical imaging sources. The dataset includes labeled ultrasound images representing different categories of ovarian cysts such as simple cysts, complex cysts, and polycystic ovarian conditions. Proper labeling of images is essential to ensure accurate model training and classification performance.

The collected dataset is carefully organized into structured categories to support supervised learning. The availability of labeled medical images enables the system to learn distinguishing visual features associated with different cyst types and improves prediction reliability during testing.

B. Data Preprocessing

Medical ultrasound images often contain noise, variations in contrast, and irrelevant background information that may affect model performance. Therefore, preprocessing plays an essential role in improving image quality and preparing the dataset for training.

The preprocessing stage includes several steps such as image resizing, normalization, noise reduction, and data augmentation. Image resizing ensures that all images have uniform dimensions compatible with deep learning model input requirements. Normalization is applied to standardize pixel intensity values and improve convergence during model training. Noise reduction techniques help remove unwanted artifacts from ultrasound images, while data augmentation techniques such as rotation, flipping, and scaling are used to increase dataset diversity and reduce overfitting.

C. Region of Interest Detection Using YOLOv8

After preprocessing, the system applies the YOLOv8 object detection model to identify and localize the region of interest within ultrasound images. YOLOv8 is a real-time object detection algorithm capable of detecting anatomical structures efficiently with high accuracy and speed.

The model processes the input ultrasound image in a single forward pass and predicts bounding boxes around potential ovarian cyst regions. This localization step ensures that the classification model focuses only on relevant regions instead of analyzing the entire image, thereby improving classification accuracy and reducing computational complexity.

D. Feature Extraction and Classification Using CNN (VGG16)

Once the region of interest is detected, the extracted image segment is passed to the classification stage based on the VGG16 Convolutional Neural Network architecture. VGG16 is a deep learning model known for its strong feature extraction capability and effectiveness in medical image classification tasks.

The classification network automatically extracts hierarchical features such as edges, shapes, textures, and structural patterns from ultrasound images. These extracted features are then used to classify ovarian cyst types into predefined categories. Transfer learning techniques are applied by using a pre-trained VGG16 model, which improves classification performance even with limited training data.

E. Model Training and Testing

The prepared dataset is divided into training and testing subsets to evaluate system performance effectively. The training dataset is used to train both the detection and classification models, while the testing dataset is used to validate prediction accuracy and generalization capability.

During training, optimization techniques such as backpropagation and gradient descent are applied to adjust model parameters and minimize classification error. Hyperparameters such as learning rate, batch size, and number of epochs are carefully selected to improve convergence and prevent overfitting. The trained model is then evaluated using unseen ultrasound images to verify its performance in real-world diagnostic scenarios.

F. Performance Evaluation Metrics

To measure the effectiveness of the proposed OvaSense system, several standard evaluation metrics are used, including accuracy, precision, recall, and F1-score. These metrics help assess classification performance and detection reliability.

Accuracy measures the overall correctness of predictions, while precision evaluates the proportion of correctly identified positive cases among all predicted positive cases. Recall measures the ability of the system to correctly identify actual cyst cases, and the F1-score provides a balanced evaluation of both precision and recall.

The use of these evaluation metrics ensures that the proposed system is reliable, efficient, and suitable for supporting clinical diagnostic decision-making.

G. System Workflow

The overall workflow of the proposed OvaSense system follows a sequential processing pipeline:

Ultrasound Image Input → Image Preprocessing → Region Detection using YOLOv8 → Feature Extraction using CNN → Classification using VGG16 → Prediction Output

This structured workflow enables automated ovarian cyst detection with improved diagnostic accuracy and reduced processing time, making the system suitable for real-time healthcare applications.

VI. Proposed System Architecture

The proposed OvaSense system architecture is designed as a hybrid deep learning-based diagnostic framework for automated detection and classification of ovarian cysts using ultrasound images. The architecture consists of multiple interconnected modules that work together to process medical images efficiently and generate accurate classification results. The system integrates image preprocessing techniques, a YOLOv8-based object detection module, and a CNN-based VGG16 classification model within a unified workflow to support real-time clinical decision-making.

The architecture follows a modular design approach to ensure scalability, flexibility, and ease of integration with existing healthcare information systems. Each module performs a specific function within the diagnostic pipeline, enabling efficient processing of ultrasound images from input acquisition to final prediction output.

A. Input Module

The input module serves as the entry point of the proposed system, where ultrasound images of ovarian regions are uploaded by healthcare professionals through a user-friendly interface. The system accepts medical images in standard formats and prepares them for further processing. This module ensures seamless interaction between users and the diagnostic framework, allowing both technical and non-technical medical staff to operate the system efficiently.

B. Image Preprocessing Module

After image acquisition, the ultrasound images are passed to the preprocessing module to improve image quality and standardize input format. This stage includes operations such as image resizing, normalization, noise removal, and contrast enhancement. These preprocessing steps help eliminate unwanted artifacts present in ultrasound images and ensure consistent input dimensions required for deep learning model training and inference.

Additionally, preprocessing enhances important visual features within the images, enabling the detection and classification models to perform more effectively during subsequent processing stages.

C. Region of Interest Detection Module (YOLOv8)

Following preprocessing, the system applies the YOLOv8 object detection model to identify and localize the region of interest containing ovarian cyst structures. YOLOv8 processes the ultrasound image using a single-stage detection approach and generates bounding boxes around suspected cyst regions with high speed and accuracy.

This localization step plays a crucial role in reducing computational complexity by focusing only on relevant anatomical regions rather than analyzing the entire image. As a result, the detection module improves classification efficiency and enhances overall diagnostic performance.

D. Feature Extraction and Classification Module (CNN–VGG16)

Once the region of interest is identified, the extracted image segment is forwarded to the classification module based on the VGG16 Convolutional Neural Network architecture. This module performs automatic feature extraction by learning hierarchical image representations such as edges, shapes, textures, and structural patterns associated with ovarian cyst types.

Transfer learning techniques are applied using a pre-trained VGG16 model to improve classification accuracy and reduce training time. The classification module categorizes ultrasound images into predefined cyst types such as simple cysts, complex cysts, and polycystic ovarian conditions. This stage forms the core decision-making component of the proposed diagnostic system.

E. Prediction and Output Module

After classification, the prediction module generates diagnostic results indicating the detected cyst type along with classification confidence levels. The results are displayed through the system interface in an easily interpretable format to assist healthcare professionals in making clinical decisions.

This module ensures that prediction outputs are delivered quickly and accurately, supporting real-time diagnostic assistance during medical evaluation.

F. Database Management Module

The database module is responsible for storing ultrasound images, patient-related metadata, and prediction results generated by the system. Maintaining a structured database enables tracking of diagnostic history and supports future analysis, system improvement, and model retraining.

The storage system also facilitates integration with hospital information systems and electronic health record platforms for efficient healthcare data management.

G. System Workflow Pipeline

The overall workflow of the proposed OvaSense system follows a sequential pipeline that ensures efficient processing and accurate classification of ovarian cyst ultrasound images:

Input Ultrasound Image → Image Preprocessing → Region Detection using YOLOv8 → Feature Extraction using CNN (VGG16) → Classification → Prediction Output → Database Storage

This pipeline enables automated ovarian cyst detection with minimal human intervention while maintaining high diagnostic reliability and processing efficiency. The modular structure of the architecture also allows future integration with cloud-based healthcare systems and telemedicine platforms, making the proposed system suitable for real-world clinical deployment.

VII. Conclusion

This research presents OvaSense, an intelligent deep learning-based diagnostic framework designed for the automated detection and classification of ovarian cysts using ultrasound images. The proposed system integrates advanced object detection and classification techniques by combining the YOLOv8 model for accurate localization of ovarian cyst regions with a Convolutional Neural Network based on the VGG16 architecture for precise classification of cyst types. The hybrid deep learning approach enables efficient feature extraction and improves the overall reliability and consistency of ultrasound image analysis.

The implementation of the proposed system demonstrates that deep learning techniques can significantly enhance the accuracy and speed of ovarian cyst detection compared to traditional manual diagnostic methods. By automating the process of region detection and classification, the OvaSense framework reduces dependency on expert interpretation, minimizes the possibility of human error, and supports faster clinical decision-making. This contributes to improving diagnostic efficiency, especially in healthcare environments with high patient workloads.

Furthermore, the use of transfer learning techniques improves classification performance even when working with limited medical imaging datasets. The integration of preprocessing techniques and region-of-interest detection ensures that the classification model focuses on relevant anatomical structures, thereby enhancing prediction accuracy and system performance. The modular architecture of the proposed system also allows easy scalability and integration into existing hospital information systems and medical imaging workflows.

The results of this study highlight the potential of artificial intelligence-based medical image analysis systems in supporting radiologists and gynecologists during diagnostic procedures. The proposed framework serves as an effective decision-support tool that can assist healthcare professionals in early detection and classification of ovarian cysts, ultimately contributing to improved patient care and treatment planning.

Although the proposed system demonstrates promising performance, its effectiveness depends on the availability and quality of annotated ultrasound datasets and computational resources required for deep learning model training. Future improvements can further enhance classification accuracy through the use of larger datasets and advanced deep learning architectures. Overall, the OvaSense system represents a reliable and scalable intelligent healthcare solution that contributes to the advancement of automated diagnostic technologies in gynecological medical imaging.

VIII. Future work

Although the proposed OvaSense system demonstrates promising performance in the automated detection and classification of ovarian cysts using ultrasound images, several opportunities exist for further enhancement and extension of the system to improve its clinical applicability and robustness.

One important direction for future research is the use of larger and more diverse ultrasound imaging datasets collected from multiple healthcare institutions. Increasing dataset diversity will improve the generalization capability of the deep learning models and enhance their performance across different imaging conditions, patient demographics, and ultrasound machine variations. The inclusion of multi-center datasets will also help validate the reliability of the proposed framework in real-world clinical environments.

Another potential improvement involves the integration of more advanced deep learning architectures such as EfficientNet, ResNet, or transformer-based vision models to further enhance feature extraction capability and classification accuracy. These architectures can provide better performance compared to traditional convolutional neural network models when applied to complex medical imaging tasks.

Future research can also explore the incorporation of explainable artificial intelligence (XAI) techniques to improve transparency and interpretability of prediction results. Providing visual explanations such as heatmaps and attention maps will help healthcare professionals better understand how the model identifies ovarian cyst regions, thereby increasing trust and usability of the system in clinical practice.

In addition, the proposed system can be extended to support advanced imaging modalities such as Doppler ultrasound and three-dimensional ultrasound imaging, which can provide richer diagnostic information and improve detection accuracy. Integrating multimodal imaging inputs may further enhance system reliability and diagnostic precision.

Another important future direction is the development of a cloud-based and mobile application version of the OvaSense framework. Such deployment would enable remote diagnosis and telemedicine support, particularly benefiting rural and underserved areas where access to expert radiologists is limited. Cloud integration would also allow continuous model updates and centralized data management for large-scale healthcare deployment.

Furthermore, the system can be expanded to detect and classify additional gynecological abnormalities such as ovarian tumors, uterine fibroids, and polycystic ovarian syndrome using the same hybrid deep learning architecture. This extension would transform the proposed framework into a comprehensive intelligent diagnostic platform for women’s healthcare.

Finally, future work may focus on integrating the OvaSense system with hospital information systems and electronic health record platforms to enable seamless clinical workflow integration. Continuous learning mechanisms can also be implemented to allow the model to improve automatically over time as new medical data becomes available. These advancements will further strengthen the capability of the proposed system and support its adoption in modern intelligent healthcare environments.

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