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AUTO-FOLLICULOMETRY CLINICAL ASSISTANT (AFCA): A U-NET BASED APPROACH FOR ULTRASOUND IMAGE SEGMENTATION

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1. **Abstract** The process of ovarian follicle measurement in IVF treatments is traditionally performed manually using ultrasound images, which is time-consuming and prone to inter-observer variability. This project proposes an AI-based system, Auto-Folliculometry Clinical Assistant (AFCA), to automate follicle detection and measurement. The objective is to improve diagnostic accuracy, reduce manual effort, and ensure consistent clinical results. The system uses a U-Net-based deep learning model with a ResNet backbone for robust image segmentation. This is paired with preprocessing techniques such as CLAHE for contrast enhancement, and post-processing using OpenCV for contour detection and precise size estimation. The proposed method enables pixel-level segmentation of follicles, allowing for the precise calculation of their dimensions. Experimental results show that the system reduces scan analysis time by approximately 50% and vastly improves measurement consistency. This approach demonstrates the strong potential of artificial intelligence in enhancing medical imaging workflows and supporting clinical decision-making.

2. **INTRODUCTION:**

Medical imaging plays a foundational role in modern healthcare, particularly in assisted reproductive treatments such as In Vitro Fertilization (IVF). Transvaginal ultrasound imaging is widely used to monitor the growth of ovarian follicles, which is essential for determining optimal treatment plans and ovulation triggers. However, current clinical methods rely heavily on manual measurement using ultrasound calipers. This conventional approach is inherently time-consuming and suffers from high inter-observer variability depending on the clinician's experience. This project addresses these critical inefficiencies in clinical workflows. The primary objective is to develop an automated system—the Auto-Folliculometry Clinical Assistant (AFCA)—that provides accurate, real-time follicle detection and measurement, standardizing clinical outputs and optimizing physician workload.

DOMAIN EXPLANATION:

The Auto-Folliculometry Clinical Assistant (AFCA) operates at the intersection of Healthcare and Artificial Intelligence, specifically applying advanced Computer Vision techniques to Assisted Reproductive Technology (ART). In the medical domain of In Vitro Fertilization (IVF), treatment success heavily relies on the precise monitoring of ovarian follicles via transvaginal ultrasound imaging to determine the optimal timing for egg retrieval. Because traditional ultrasound scans are inherently noisy and manual caliper measurements are subjective, time-consuming, and prone to human error, this project leverages Deep Learning to automate the entire workflow. By utilizing a U-Net architecture for pixel-level semantic segmentation and OpenCV for exact geometric contour analysis, the system processes low-contrast medical images to automatically isolate and measure follicular fluid. Ultimately, this domain fusion transforms a manual, subjective medical task into an objective, AI-driven computational process that significantly enhances diagnostic accuracy and workflow efficiency..

1. MODULES AND IMPORTANT TECHNIQUES :

Module 1: Image Preprocessing

- **Description:** Raw ultrasound images are often degraded by speckle noise and poor lighting, making it difficult for the model to distinguish between follicles and background tissue. This module prepares the input data for accurate analysis.
- **Important Technique: Contrast Limited Adaptive Histogram Equalization (CLAHE).** This technique enhances the local contrast of the ultrasound images, sharpening the edges of the dark follicular fluid regions while preventing the over-amplification of noise.

Module 2: Deep Learning Segmentation

- **Description:** This is the core engine of the AFCA system. It takes the preprocessed ultrasound image and isolates the exact regions where follicles are present by classifying every single pixel.
- **Important Technique: Semantic Segmentation using U-Net with a ResNet Backbone.** Built using PyTorch, this deep learning architecture uses an encoder (ResNet) to extract deep spatial features and a decoder to construct a precise, high-resolution binary mask indicating the exact boundaries of the follicles.

Module 3: Post-Processing and Measurement

- **Description:** This module translates the binary masks generated by the AI model into actionable clinical data (physical measurements).
- **Important Technique: Computer Vision Contour Extraction.** Using the OpenCV library, the system detects the edges (contours) of the segmented masks. It then fits bounding geometries to these contours to calculate the maximum diameter of each follicle, effectively converting pixel area into standard clinical measurements (millimeters).

Module 4: User Interface and Deployment

- **Description:** To make the tool accessible to reproductive endocrinologists and sonographers without requiring coding knowledge, the backend pipeline is wrapped in a user-friendly frontend application.
- **Important Technique: Web-Based Prototyping using Streamlit.** This framework is used to build an interactive dashboard where clinicians can easily upload ultrasound scans, visualize the segmented results in real-time, and download the automated measurement reports.

2. EXISTING SYSTEM OR EXISTING CHALLENGES :

The Existing Clinical System Currently, the standard clinical practice for ovarian follicle monitoring during IVF treatments relies entirely on manual assessment. Reproductive endocrinologists or trained sonographers perform transvaginal ultrasound (TVUS) scans to visualize the ovaries. During the scan, the operator must manually freeze the ultrasound video feed, visually identify each individual follicle, and use the ultrasound machine's built-in digital caliper tool to trace the longest and shortest diameters of the follicles. This manual logging is repeated for every visible follicle across both ovaries to estimate their growth.

Key Challenges in the Existing System

- **Time-Consuming and Labor-Intensive:** Manually scanning, freezing, and measuring multiple follicles (often 10 to 20 per patient) is a highly tedious process. It adds significant time to each patient consultation, reducing the overall workflow efficiency of the IVF clinic and causing fatigue for the medical staff.
- **High Inter-Observer and Intra-Observer Variability:** Because the measurement relies entirely on human eyesight and judgment, the results are highly subjective. Two different doctors

might measure the exact same follicle differently (inter-observer variability), or even the same doctor might measure it differently at different times (intra-observer variability). This inconsistency can lead to suboptimal decisions regarding when to trigger egg retrieval.

- **Poor Image Quality and Speckle Noise:** Ultrasound images are inherently noisy. They suffer from acoustic shadowing, low contrast, and high speckle noise. In the existing manual system, these artifacts often obscure the true boundaries of the follicles, making it extremely difficult for the human eye to determine exactly where the follicle wall begins and ends.
- **Failure of Traditional Semi-Automated Tools:** While some older software tools attempt to assist doctors using traditional image processing techniques (like basic thresholding or watershed algorithms), they frequently fail. These traditional algorithms cannot handle the complex noise of ultrasound images or effectively separate overlapping follicles, rendering them unreliable for daily clinical use.

3. PROPOSED SYSTEM OR PROJECT:

- **Login Authentication System** – Secure access control ensuring only authorized medical personnel and clinicians can enter the application.
- **Image Upload & Preprocessing System** – Enhances raw ultrasound scans using CLAHE to reduce speckle noise.
- **Deep Learning Segmentation Engine** – Detects and isolates ovarian follicles at the pixel level using a U-Net model.
- **Automated Measurement Module** – Calculates precise follicle dimensions using OpenCV contour detection.
- **Real-Time Visualization Dashboard** – Displays segmented masks and bounding boxes directly over the original ultrasound images.
- **Automated Clinical Reporting** – Generates tabulated summaries of follicle counts and sizes for quick medical review.
- **Interactive Streamlit Interface** – User-friendly and responsive web interface designed specifically for clinical staff.

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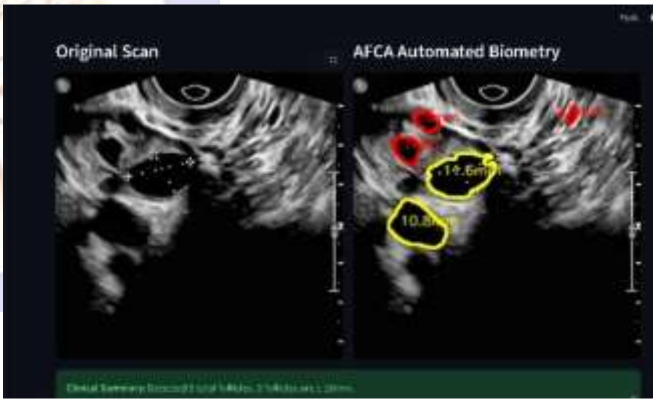


4. SOFTWARE AND HARDWARE REQUIREMENTS:

4.1. SOFTWARE REQUIREMENTS:

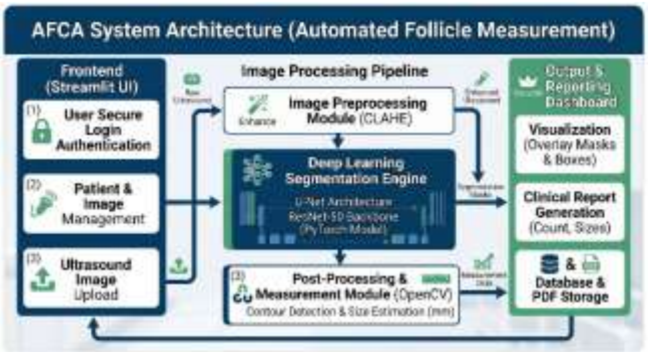
Hardware Requirements:

- **Processor:** Intel Core i5 / AMD Ryzen 5 or higher
- **RAM:** 8 GB minimum (16 GB recommended)
- **Storage:** 256 GB SSD
- **GPU:** NVIDIA GPU with 4GB+ VRAM (Recommended for faster deep learning processing)

Software Requirements:

- **Operating System:** Windows, macOS, or Linux
- **Programming Language:** Python 3.8+
- **Deep Learning Framework:** PyTorch
- **Computer Vision & Processing:** OpenCV, NumPy, Pandas
- **Web Interface:** Streamlit
- **IDE:** VS Code / PyCharm / Jupyter Notebook

5. ARCHITECTURE DIAGRAM:



5.1. EXPLANATION:

5.1.1. PRODUCT DETAILS:

- **PRODUCT NAME:** Auto-Folliculometry Clinical Assistant (AFCA)

- **PRODUCT TYPE:** AI-Powered Medical Imaging Software / Web Application

- **TARGET USERS:** IVF Clinics, Gynecologists, Reproductive Endocrinologists, and Medical Sonographers.

- **CORE PURPOSE:** To replace manual ultrasound follicle tracking with an automated, deep-learning-based segmentation and measurement pipeline.

- **KEY FEATURES INCLUDED:** * **Secure Access:** Login authentication for authorized clinical staff.

  - **Patient Management:** System to store and manage patient ultrasound records securely.
  - **AI Processing Engine:** Automated follicle detection and sizing using U-Net and OpenCV.
  - **Automated Reporting:** PDF clinical report generation using ReportLab.
  - **Interactive Dashboard:** User-friendly visualization and analytics interface built on Streamlit

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6. RESULT:

[1] The login page serves as the primary security gateway, utilizing credential validation to authenticate users before granting access to the Streamlit-based clinical dashboard Fig.7.1.

Fig.7.1.

[2] Adding the Ultrasound image to get the measurements Fig.7.2.

Fig.7.2.

[3] Uploads the ultrasound scan to automatically generate and display follicle diameter measurements. as shown in Fig.7.3.

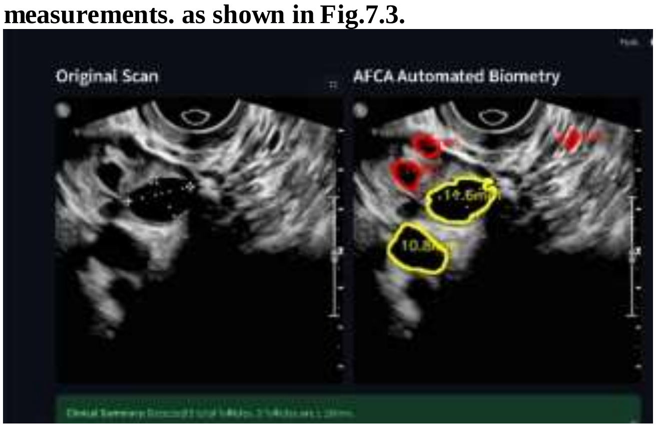
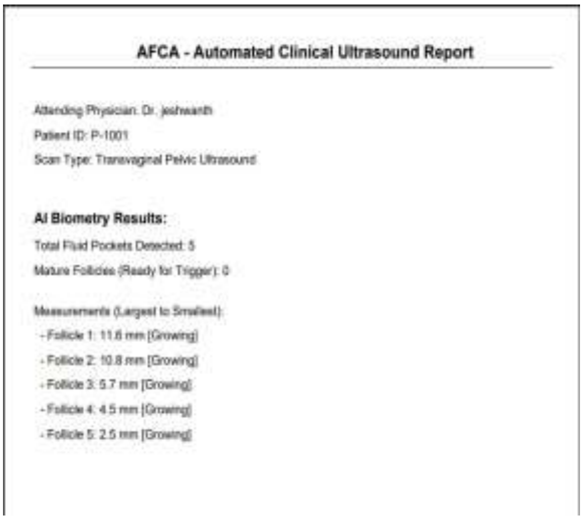


Fig.7.3.

[4] Exports and downloads the final measurement results as a PDF clinical report Fig.7.4.


AFCA - Automated Clinical Ultrasound Report

Attending Physician: Dr. jeshwanth
Patient ID: P-1001
Scan Type: Transvaginal Pelvic Ultrasound

AI Biometry Results:
Total Fluid Pockets Detected: 5
Mature Follicles (Ready for Trigger): 0

Measurements (Largest to Smallest):
- Follicle 1: 11.6 mm [Growing]
- Follicle 2: 10.8 mm [Growing]
- Follicle 3: 5.7 mm [Growing]
- Follicle 4: 4.5 mm [Growing]
- Follicle 5: 2.5 mm [Growing]

Fig.7.4.

[5] An integrated Electronic Health Records (EHR) Directory that securely stores patient biometry data, tracks follicle maturity, and supports full database exports to CSV format. as shown in Fig.7.5.

Fig.7.5.

7. CONCLUSION AND FUTURE ENHANCEMENT:

The Auto-Folliculometry Clinical Assistant (AFCA) successfully addresses the critical inefficiencies and subjective variations inherent in manual ovarian follicle measurement during IVF treatments. By integrating a ResNet-backed U-Net deep learning architecture with advanced computer vision techniques (CLAHE and OpenCV), the system achieves highly accurate, pixel-level segmentation and precise dimension estimation of follicles. The deployment of this pipeline through an intuitive, interactive Streamlit interface provides a seamless experience for medical professionals, requiring no technical background to operate. Ultimately, this project demonstrates that AI-driven medical imaging tools can reduce scan analysis time by approximately 50%, eliminate inter-observer variability, and significantly enhance workflow efficiency and clinical decision-making in reproductive endocrinology.

Future Enhancements While the current AFCA system is highly effective for 2D ultrasound analysis, several enhancements can be implemented to scale the project for wider clinical adoption:

- **3D Ultrasound Integration:** Extending the AI model to process 3D ultrasound volumes, allowing for complete volumetric calculation of the follicles rather than just 2D cross-sectional diameters.
- **Longitudinal Growth Tracking:** Developing a predictive analytics module to track and graph the growth rate of individual follicles across multiple days, helping doctors predict the exact optimal day for egg retrieval.
- **PACS/DICOM Integration:** Upgrading the system to directly interface with hospital Picture Archiving and Communication Systems (PACS) via the DICOM standard. This would allow the software to pull scans directly from the ultrasound machine without manual uploads.
- **Cloud Deployment:** Migrating the locally hosted Streamlit application to a secure, healthcare-compliant cloud platform (such as AWS or Google Cloud) to enable remote access and multi-clinic collaboration.
- **Mobile Application:** Developing a companion mobile or tablet application so clinicians can quickly review automated follicle reports, PDF invoices, and patient analytics on the go.

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