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UNA: Uterine Neoplasm Analyzer Detecting the Cancer Tumor Using Advanced Image Analysis

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ABSTRACT: The **Uterine Neoplasm Analyzer (UNA)** is a machine learning-driven application designed to aid in the early detection and analysis of uterine neoplasms (tumours) through medical imaging and patient symptom data. This innovative system leverages Python and advanced ML algorithms to process and analyse ultrasound and sonography images of the uterine region. By applying specialized image filters, UNA extracts critical features from medical images, enabling the identification of abnormalities indicative of cancerous growths. In addition to image analysis, the system integrates patient-reported symptoms, utilizing a comprehensive decision-making model to enhance diagnostic accuracy. The application outputs a binary prediction (0 for non-cancerous, 1 for cancerous) and highlights key features on the analysed image, providing visual feedback to medical professionals. UNA's approach bridges imaging technology with machine learning to offer an efficient, accurate, and user-friendly tool for preliminary diagnosis, thus supporting early intervention and improved patient outcomes. This project underscores the potential of AI in revolutionizing healthcare diagnostics while aligning with precision medicine principles.

KEYWORDS: UNA, Neoplasm, Tumor, Symptoms, Diagnostic, Preliminary Diagnosis, Endometrial.

I. INTRODUCTION

Endometrial cancer is the most common malignancy seen in the lower female genital tract in the western industrialized world. The disease occurs during the reproductive and menopausal years and it is highly dependent on age with the vast majority of patients being between 50 and 59 years old. Although an increase in the number of patients with endometrial cancer was noted in recent years, it is uncommon in premenopausal women, with a reported incidence which varies between 1.5% and 14.4% . Especially in women younger than 30 years, the disease is extremely rare. Increasing data suggests that endometrial cancer in these women is often associated with early-stage and highly differentiated tumor and usually has a good prognosis.

We report on two cases of endometrial cancer in women aged 22 and 28 years old, respectively, who underwent treatment in our Hospital, emphasizing the importance of maintaining a high index of suspicion of the disease in such young patients despite the absence of clinical or epidemiologic risk factors [1]

II. RELATED WORK

Ultrasound is often one of the first tests used to look at the uterus, ovaries, and fallopian tubes in women with possible gynecologic problems. Ultrasound uses sound waves to take pictures of the inside of the body. A small wand (called a transducer or probe) gives off sound waves and picks up the echoes as they bounce off the organs. A computer translates the echoes into pictures.

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For a **pelvic ultrasound**, the transducer is moved over the skin of the lower part of the belly (abdomen). Often, to get good pictures of the uterus, ovaries, and fallopian tubes, the bladder needs be full. That's why women getting a pelvic ultrasound are asked to drink lots of water before the test.

A **transvaginal ultrasound** (TVUS) is often better to look at the uterus. For this test, the TVUS probe (that works the same way as the ultrasound transducer) is put into the vagina. Images from the TVUS can be used to see if the uterus contains a mass (tumor), or if the endometrium is thicker than usual, which can be a sign of endometrial cancer. It may also help see if cancer is growing into the muscle layer of the uterus (myometrium).

A small tube may be used to put salt water (saline) into the uterus before the ultrasound. This helps the doctor see the uterine lining more clearly. This procedure is called a **saline infusion sonogram** or **hysterosonogram**. (Sonogram is another term for ultrasound.)
Ultrasound can be used to see endometrial polyps (growths) , measure how thick the endometrium is, and can help doctors pinpoint the area they want to biopsy.
Chemotherapy is used to treat certain types of uterine cancer, or when cancer comes back after surgery or radiotherapy, or if the cancer is not responding to hormone treatment. It can be used to control the cancer and to relieve symptoms. It is usually given as a drug that is injected into a vein (intravenously). The doctor will explain the chemotherapy treatment course and how long it will last .[2]

III. UNA: DEFINITION AND DIAGNOSIS

Definition: The differential diagnoses confronted in the evaluation of common endometrial cancer presenting symptoms and signs (eg, abnormal vaginal bleeding and pelvic masses) range from benign localized lesions to systemic diseases and malignancies. The FIGO classification of abnormal uterine bleeding should be used to help guide differential diagnoses evaluation, which comprises polyps, adenomyosis, leiomyoma, malignancy, coagulopathy, ovulatory dysfunction, primary endometrial disorders, iatrogenic, and not classified (PALM-COEIN). Furthermore, the evaluation of AUB in premenopausal women should include intrauterine and ectopic pregnancies and gestational trophoblastic diseases.

Exogenous hormone stimulation (eg, estrogen, progesterone and progestogens, androgens, and tamoxifen) of the endometrium may cause AUB in premenopausal and postmenopausal women. Ovulatory dysfunction results from systemic and endocrinologic causes (eg, anorexia, obesity, and polycystic ovarian disease), hilar cell hypertrophy and hormone-secreting tumors of the ovary, thyroidopathies, adrenal hyperplasia and tumors, and pituitary tumors should be considered. Signs of defeminization, hirsutism, and alopecia may mark endocrinopathies associated with excess androgen secretions. Differential diagnoses of physically detected pelvic masses include metastatic cancer, hydrosalpinx, fallopian tube tumors, ovarian and broad ligament cysts and tumors, leiomyomas, postsurgical pelvic adhesions, retroperitoneal kidneys, dermoid tumors, tumorous nodes, primary colorectal and gastrointestinal cancers, and urological masses.[3]

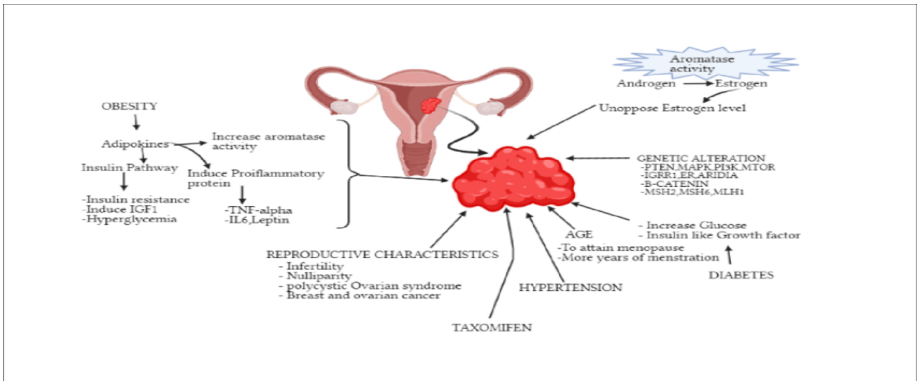

Figure 1: Anatomical structures of the Women Uterus Cancer and hormonal imbalance, genetic alterations, reproductive characteristics, diabetes, and hypertension.

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IV. UNA DIAGNOSIS PROCEDURE

UNA Signs of uterine cancer can resemble those of many conditions. That's especially true of other conditions affecting reproductive organs. If you notice unusual pain or irregular vaginal bleeding, talk to your healthcare provider. An accurate diagnosis is important so you can get the proper treatment.
Step 1: **Initial Consultation:** Review symptoms (bleeding, pain, discharge) and medical history (family cancer history, hormonal therapy).
Step 2: **Physical Examination:** Pelvic exam to check reproductive organs for abnormalities.
Step 3: Diagnostic Tests: Transvaginal Ultrasound (TVUS): Measures uterine lining thickness.
Endometrial Biopsy: Tissue sample for cancer confirmation.
Hysteroscopy: Visualizes and samples uterine lining.
Step 4: Imaging Tests:
MRI: Checks cancer extent and spread.
CT/PET Scans: Detects distant spread.
Chest X-Ray: Looks for lung involvement.
Step 5: **Advanced Testing (If Needed):** D&C: Scrapes uterine lining for more tissue.
CA-125 Test: Blood marker for advanced cancer.
Step 6: Staging Procedures: Surgical Staging: Removes uterus, ovaries, and lymph nodes for analysis.
Pathology: Confirms stage and grade of cancer.
Step 7: **Final Diagnosis and Staging:** Stage I-IV: Assesses spread from uterus to other areas.
Step 8: Treatment Planning: Options include surgery, radiation, chemotherapy, hormone, or targeted therapy.

V. VISUAL ASPECTS OF UTERINE CANCER IMAGES

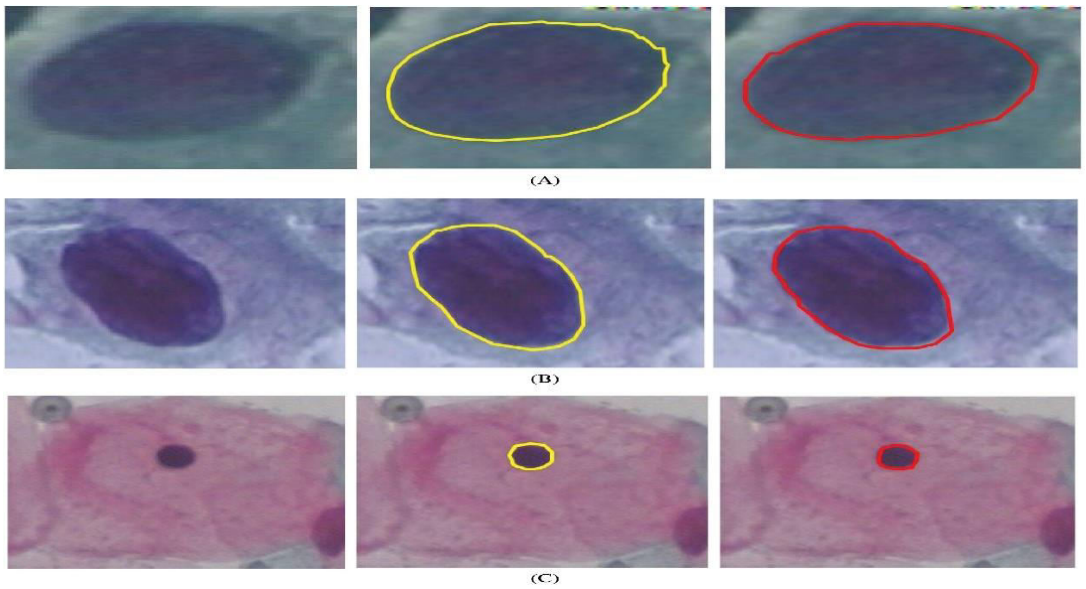

Fig 2: Retinal image

Conventional image processing techniques require human expertise in selecting and extracting visual (or pixel-based) features that separate the cervix region from non-cervix regions. They are hampered by: (i) variability in image appearance (e.g., presence of blood, specular reflection from the moistened tissue, texture variation due to pathology, and occlusion due to medical instruments); and, (ii) feature selection and representation for maximizing discrimination between the cervix region from non-cervix regions. In , K-means clustering and Otsu's method are applied to extract the cervix region after the step of specular reflection removal, by replacing the region with patches of similar texture and color. The segmentation is based on thresholding pixel values in HSV and LAB color space, which might not be robust across data sets when either color or lighting condition changes. An IoU score of 0.79 is reported in . In , cervix

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segmentation serves as the first step for the cervix image registration workflow; similar to , a fuzzy C-means clustering approach is employed for cervix segmentation and is reported to achieve an average IoU score of 0.76. In , cervix images captured using cell-phone cameras are segmented through the combination of edge detector, red-color component filter, curvature filter, and thresholding. The researchers report an average Dice score of 0.9, on a small set of 151 images. Curvature features are used in with additional information provided by shape priors, the proposed curve evolution with the shape prior model achieves an average Dice measure of 0.81. In addition to the above image processing techniques, statistical modeling methods have also been employed for cervix segmentation in the literature. In , the probability function is defined by adding a circular/elliptical prior to the existing framework with K-means clusters from . The model is shape-based in which the cervix can be considered either as circular or elliptical, and the reported average Dice score is 0.75. In , the probability of a pixel being part of cervix is calculated by maximizing the likelihood function. The performance measure used in is the ROC (receiver operating characteristic) curve which has an AUC (area under curve) with approximate value 0.9 and is obtained from 250 sample images acquired from only 4 patients. Sparse representation and group sparsity based feature selection are employed in to segment the biomarker acetowhitened area on cervix, and a sensitivity improvement of 0.12 and specificity of 0.05 is achieved using discriminative sparse representation compared with the sparse representation approach used in . [4]

VI. FEATURE EXTRACTION FROM TUMOR IMAGES

Feature extraction is the next step after preprocessing. In early papers, only shape-based features and some basic texture-based methods were used to extract the features after segmentation and preprocessing of an image. However, in this paper, the texture of the image is analysed, and high-order derivatives are used to find the features. So, the cells are classified according to that texture in normal and cancerous cell. Feature extraction is the first stage of image texture analysis. In this paper, texture-based features are extracted using first-order histogram GLCM LBP laws texture energy based (Laws) and discrete wavelet transform (DWT). By using the first-order histogram, these six features are extracted: mean, variance, skewness, kurtosis, energy, and entropy of grey image. GLCM gives these five extracted features: energy, correlation, homogeneity, entropy, and contrast. By using LBP, 256 bins are generated for all images. By calculating the mean and variance of 256 bins, total two features are extracted using LBP. Laws provide nine energy images for every single image. The mean value of every image is calculated using energy maps. DWT gives two features: mean and variance after decomposition of the image using low-pass filters and high-pass filters. Finally, total 24 features are extracted using all texture-based features.

VII. EVALUATION METRICS AND DATASETS

Evaluation metrics: In any uterine cancer diagnosis project, evaluation metrics are crucial for measuring the performance of the model and ensuring reliable predictions. Below are common metrics:
Evaluation Metrics:

Accuracy: Proportion of correct predictions (cancerous vs. non-cancerous) over total predictions.
Formula: Accuracy
(TP + TN)/ (TP + TN + FP + FN)
(TP + TN)/(TP + TN + FP + FN).
TP+TN+FP+FN
TP+TN

Precision : Measures the proportion of correctly identified positive cases among all predicted positives.
Formula: Precision
TP / (TP + FP)
TP+FP

Recall (Sensitivity) : Indicates the ability of the model to correctly identify actual positive cases.
Formula: Recall
TP / (TP + FN)
TP / (FN +TP)

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Specificity : Measures the ability of the model to identify true negative cases.
Formula: Specificity
TN / (TN + FP)
TN FP + TN

F1-Score: Harmonic mean of Precision and Recall, especially useful for imbalanced datasets.
Formula: F1-Score
2 ×(Precision×Recall)/(Precision+Recall)

ROC-AUC (Receiver Operating Characteristic - Area Under Curve):
Measures the trade-off between true positive rate (sensitivity) and false positive rate (1-specificity).
Higher AUC indicates better performance.
Confusion Matrix
Provides a detailed breakdown of TP, FP, TN, and FN, offering a comprehensive view of model performance.

VIII. TRANSFER LEARNING WITH CONVOLUTIONAL NEURAL NETWORKS (CNN)

As mentioned earlier, we investigate two state-of-the-art deep learning architectures, viz., Mask R-CNN and MaskX R-CNN, for the cervix segmentation problem. We categorize our datasets into strongly or weakly labeled subsets (mask and box). Strongly labeled sets have fine cervix boundaries from which we derive masks of the cervix region, while weakly annotated sets have only the bounding box around the cervix region. Mask R-CNN can only be trained using strongly annotated data; however, MaskX R-CNN can be trained using both dataset types.

For example, we train a MaskX R-CNN model on a combination of weakly annotated data and strongly annotated data that was also used to train the Mask R-CNN model. We compare the segmentation results using five strategies. simple single- and cross-dataset training and testing: training and testing data is sourced from only one dataset, but the dataset used for training or testing could be different; boosting with bounding box information: evaluate segmentation performance when adding weakly annotated images to a strongly annotated training set; modified weak annotations: where bounding boxes are relaxed to include neighboring pixels to allow uncertainty in expert observer annotation; multi-dataset training and testing: training and/or test data are pooled from multiple datasets; different training strategies: where training is done end-to-end or stage-wise; and, both Mask R-CNN and MaskX R-CNN, described below, are built on an underlying “backbone” network (e.g., ResNet50, ResNet101) that we compare results across.

Mask R-CNN

Mask R-CNN is an extension of the Faster R-CNN deep learning architecture for segmentation of object “instances” in an image. It adopts the same two-stage procedure as Faster R-CNN, where the first stage is a Region Proposal Network with a Feature Pyramid Network structure, followed by a second stage predicting the class and bounding box in parallel. In addition, a mask branch is added in the second stage which is used to predict binary masks of the objects, yielding finer spatial definition. A feature pyramid structure extracts features on different scales for both the region proposal and classification. This may aid in improving accuracy and speed compared with single-scale feature map structures. Furthermore, a novel image region of interest (RoI) alignment technique, RoIAlign , is applied to compute the exact values of the input features at four regularly sampled locations in each evenly split RoI bin. Bilinear interpolation is employed to avoid the information loss brought by simply pooling and quantizing. Since the supervised architecture requires training with strongly annotated image data, we focus on training and testing Mask R-CNN using single or multiple datasets where mask ground truth is available (i.e., $Am\times a\times s\times k$, $Bm\times a\times s\times k$, and $Cm\times a\times s\times k$).[5]

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IX. RESULT

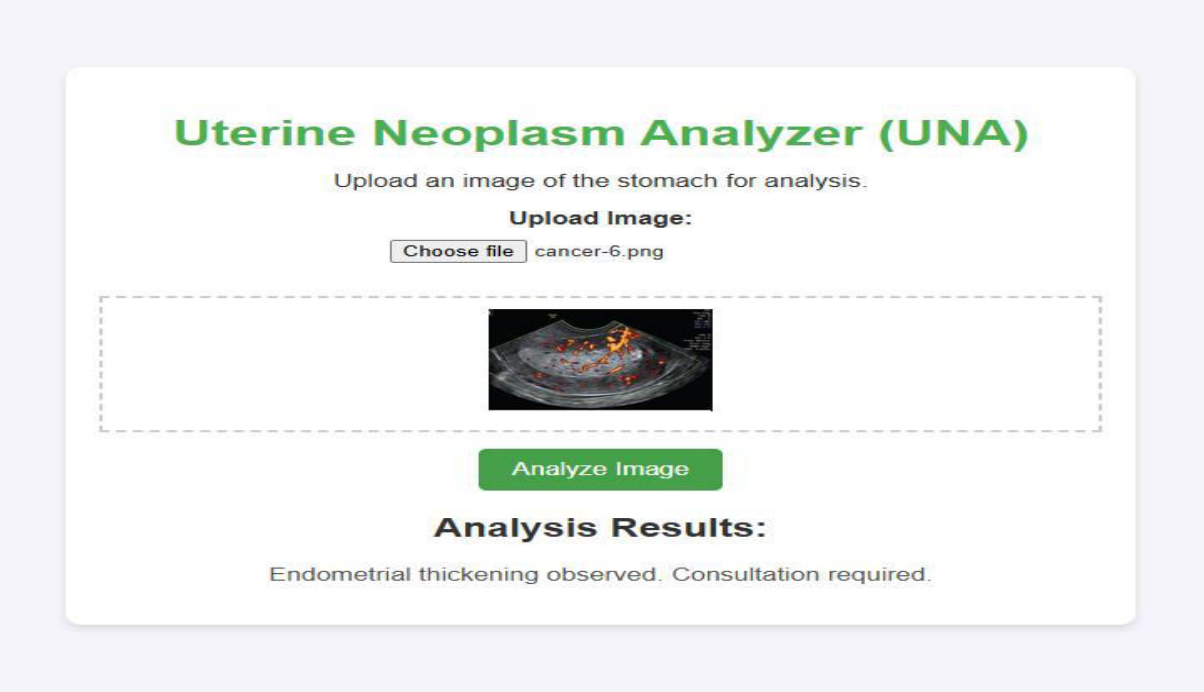

Fig 3: First Image

X. CONCLUSION

The **Uterine Neoplasm Analyzer (UNA)** represents a significant advancement in the early detection and diagnosis of uterine cancer. By integrating advanced image processing techniques, such as ultrasound filtering, with AI-powered predictive models, UNA offers a comprehensive tool to assist medical professionals in identifying the presence and stage of uterine neoplasms with high accuracy.

This project demonstrates the potential of technology to revolutionize healthcare, providing timely and reliable analysis to improve patient outcomes. UNA's robust architecture ensures scalability, enabling it to analyze large datasets efficiently while maintaining high accuracy. The system's adaptability to evolving medical imaging standards ensures its relevance and effectiveness in future diagnostic practices.

Furthermore, the user-friendly interface of UNA ensures accessibility for both experienced and novice healthcare professionals, reducing the learning curve associated with adopting new technologies. By incorporating real-time analysis and stage-wise classification, UNA helps optimize treatment planning, improving the quality of care provided to patients.

As UNA continues to evolve, its ability to handle diverse datasets, integrate additional imaging modalities, and provide detailed insights will enhance its diagnostic precision and usability. Ultimately, UNA not only aims to support healthcare practitioners but also to empower patients by facilitating early intervention, enabling personalized treatment plans, and improving the overall management of uterine cancer.

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