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Research Article

Enhanced Classification of Endometrial Carcinoma Using Machine Learning Powered by Explainable AI

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Abstract:
Magnetic Resonance Imaging plays a vital part in diagnosis of mutant cells in the endometrial layer of women reproductive system. This Endometrial carcinoma (EC) is one among the type of uterine cancer acts as a major challenge for the medical practitioners for early diagnosis and classification. This study explores advanced imaging techniques and artificial intelligence (AI) for improved EC identification. The Methodology incudes, an approach of extracting texture features using Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), and Gray Level Run Length Matrix (GLRLM) from the image data. These features are fused using a hybrid approach to capture complementary information. Machine learning classifiers including Random Forest (RF), Radial Basis Function (RBF), Artificial Neural Network (ANN), Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Adaptive Neuro-Fuzzy Inference System (ANFIS) are trained and evaluated. Results demonstrate significant improvements in classification accuracy, with the hybrid feature extraction method achieving significant accuracy. Explainable AI (XAI) techniques are employed to interpret and visualize classifier decisions, providing details into the discriminative features contributing to EC classification.. The findings support the potential of integrating advanced imaging and machine learning, facilitated by XAI, for precise EC diagnosis and therapeutic planning.

Keywords: Endometrial carcinoma, Machine Learning, Explainable AI, Texture Feature Extraction ,Magnetic Resonance Imaging

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I. INTRODUCTION

Women's reproductive system is commonly affected by certain infections or diseases among which Uterine cancer founds to be very riskier comparatively. Endometrial carcinoma or uterine sarcoma is commonly referred as uterine cancer. This carcinoma that occurs in the inner lining wall of uterus called as endometrial layer is the most common type of gynecological cancer where as uterine sarcoma generally develops in the myometrial layer is less common among women. Unusual pain, irregular vaginal bleeding, clear vaginal discharge are few symptoms of the endometrial carcinoma. Based on the balance between estrogen and progesterone risk factors various widely. The most serious complication of uterine cancer may lead to death.

Early diagnoses by the healthcare providers at the early stage can lead to better prognosis. Physical exam and the pelvic exam are the tests that can considered for the early diagnosis of uterine cancer. With the rapid growth in the medical and technical developments, diagnosis of the mutant cells is found to be more precise and accurate. Though blood test measuring CA-125, endometrial biopsy, hysteroscopy proves to be efficient medical diagnosing methods, an added support by the development in field of diagnosing instruments supports health care providers an ease in early diagnosis of the diseases. Imaging test using Computer Tomography, Magnetic Resonance Imaging, Transvaginal ultrasound gives a detailed studied in the interiors of human body. These detailed studies support the medical practitioners to find the type of variants and stage in which the disease actually sustains.

Magnetic Resonance Imaging uses radio waves and powerful magnets to produce images. Preoperative MRI evaluation of patients with endometrial carcinoma varies internationally.

American College of Radiology suggests MRI should be the preferred imaging modality for treatment planning as it allows better assessment of the disease. MRI was considered as the potent imaging tool that assist in triage treatment in women affected by endometrial carcinoma. MRI also assist medical practitioners in correct planning of their treatment. Optimization of the imaging techniques can be performed for endometrial carcinoma staging and accuracy of locally spread tumor [1].

Image analysis using machine learning algorithms supports to a greater extent in the medical field. Reasonable diagnoses were able to be carried out using these methods. This paper uses the feature extraction methods such as Gray-level Correlation Matrix(GLCM),Gray level Run Length matrix(GLRLM),Histogram of Oriented Gradients (HOG),Local Binary Pattern(LBP).Individually the above techniques covers a wide set of features that can be extracted for medical imaging method of Carcinoma identification.

In this article four techniques namely LBP, GLCM, HOG and GLRLM were used for feature extraction. Additionally, Features obtained were combined to form a Hybrid Feature Set. Machine Learning algorithms such as Extreme Learning Machine, Adaptive Neuro-Fuzzy Inference System, Radial Basis Function, Random Forest, Support Vector Machine are used for classification. The study uses two major image databases from The Cancer Imaging Archive to examine Uterine Corpus Endometrial Carcinoma (UCEC). The main dataset, provided by the National Cancer Institute Clinical Proteomic Tumor Analysis Consortium (CPTAC), includes 600 images. This set has 400 images of UCEC tumours and 200 images of normal tissue (National Cancer Institute Clinical Proteomic Tumor Analysis Consortium [CPTAC], 2019).

To improve this dataset, detailed annotations from Rozenfeld and Jordan (2023) were added. These annotations give important information about the tumours, making the primary dataset more useful for analysis. The annotated dataset includes 250 images, mostly focusing on the abnormal images. The images were downloaded individually with their annotations and augmented to increase the size of the dataset. As the required size of these datasets was less, it was found difficult for deep learning and so machine learning algorithms were considered with handcrafted features for image classification. The contribution of this article involves

- A framework consisting of Hybrid Feature Set was proposed followed by classification of Endometrial Carcinoma.
- Individually feature extraction techniques was analysed and compared with the proposed Hybrid Feature Set, which is a fusion of LBP+HOG+GLCM+GLRLM.
- Classification of Endometrial Carcinoma using various Machine Learning classifiers was performed.
- Performance of these classifiers are evaluated by different Performance metrices.
- Hybrid Feature Set was proposed in a motive to capture the multiple factors of the images including edges, textures, patterns. Interpretability of our machine learning models was enhanced using Explainable AI.

The Combination of LBP, HOG, GLCM, GLRLM supports in improving the accuracy, Sensitivity and other parameters. This is a common approach in computer vision applications and image processing. Benefits and drawbacks of each techniques were analyzed and found that the hybrid feature set overcomes these limitations. GLCM was very sensitive to the spatial pixel intensity whereas GLRLM was invariant to directions. But both these techniques were limited in performance for capturing the edge information's, which was mainly complimented by HOG technique. LBP by itself is an effective algorithm used in pattern recognition and computer vision. This article focuses on the performance of the classifier with different datasets analyzing individual technique as well as hybrid feature set and concludes that the proposed feature set have proved to be best comparatively. To capture feature along multiple aspects was the motivation of this proposed work. Even though this is a common approach in computer vision and image processing, this work enhances the combinational structure of feature extraction by different techniques combined together. Furthermore, this work lights out the strengths and limitations of individual techniques and the hybrid work. The article is organized with section 2 as the related works, section 3 describes the Proposed Methodology and section 4 states the results and discussions.

II RELATED WORKS

Classification of Endometrial Carcinoma can be majorly approached by two methods. The first method is to use the machine learning algorithms with the handcrafted features extracted using different techniques such as GLCM, GLRLM, Gabor features etc., These extracted features are fed to the classifiers for classification and their performance are evaluated by finding various performance metrices. Another method is by using Deep learning models for extraction of features and classification. Though Deep learning method yields high accuracy, need of huge datasets remains to be major drawback of this method. Interpretability of the results is also said to be major limitations in this method. As the size of the dataset is less, we use the first method for the Endometrial Carcinoma Classification.

Athraa H. Farhan et al, conducted research on breast cancer identification using feature extraction techniques like Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP). Mass tissue in mammograms were analyzed using these methods. These data were collected from Mini-MIAS database. The research aimed to upgrade the diagnostic accuracy by using Contrast Limited Adaptive Histogram Equalization (CLAHE) for pre-processing. The better results were achieved with the LBP method of feature extraction, classified by logistic regression classifier. 92.5% accuracy was achieved. However, the drawback shows that the results changes significantly depending on the region of interest (ROI) size and type of abnormality. Lack of important details was observed when there is a smaller ROI size, and feature extraction methods tends to have drawbacks in certain abnormal cases [2].

Wei Mao et al., developed a deep learning-based method for automatic staging of early endometrial cancer using MRI images. U-net model was trained to segment the uterine and tumor regions, using the ratio of tumor-to-uterus (TUR). This is considered as one among the other parameters for staging. 117 patients' datasets were considered for testing and training. The method achieved high accuracy, with the better results for sagittal T2-weighted MRI images. The automating of the staging process has made an important contribution in reducing radiologists' workload. However, drawbacks include the small dataset size and the model's limitations in distinguishing pelvic effusions from tumors, leading to occasional false positives [3].

Aiko Urushibara et al, developed and compared the performance of convolutional neural networks (CNNs) for diagnosing endometrial cancer using MRI images. 388 patients' datasets were used to train CNN models on single and combined image sets, that includes T2-weighted images, ADC maps, and contrast-enhanced images. The CNNs achieved an AUC ranging from 0.88 to 0.95, which was comparable or even dominating to radiologists in few cases. However, the drawbacks include the use of JPEG images instead of DICOM, which could have reduced data quality. Additionally, only selected images were used, that differs from clinical practice where series of images are analyzed

The gap identified from the referenced studies is that primarily major works depends on deep learning models, which automatically extract features but might lack in important handcrafted features like texture or shape. A major gap identified in the referenced studies is the lack of focus on explainability. Deep learning models, though powerful and often function as "black boxes." The use Explainable AI (XAI) provides clarity on how and why decisions are made, that supports for greater transparency and clinical trust in the results. A more comprehensive analysis of model performance across different approaches is also made.

III PROPOSED METHODOLOGY

Flow Diagram:

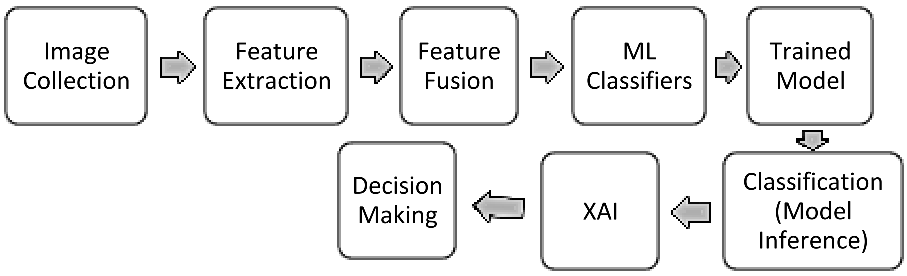

Figure 1: Flow diagram of the proposed system

The figure 1 flow diagram represents various stages involved in our research methodology for image-based uterine cancer prediction using machine learning powered by Explainable AI (XAI) technique. Initially, the collected MRI uterine images with endometrial carcinoma, serves as the raw data for the further work. The quality and type of image is important as they directly impact the accuracy and effectiveness of the subsequent analysis. Various feature extraction techniques such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), and Gray Level Run Length Matrix (GLRLM) are applied to these images to extract the required features. Each method captures various aspects of images such as texture and structure, essential for accurate classification. The features extracted are then combined through a feature fusion process, creating a comprehensive feature set that influences the corresponding information to enhance the robustness and discriminative nature of the classifiers.

Following feature fusion, machine learning models are trained using the hybrid feature set. Various classifiers such as ANN, ANFIS, and RF are trained to predict outcomes based on the extracted features. The trained models are then applied to new, unseen data for making predictions. To enhance the interpretability of the model predictions, XAI techniques such as layer-wise relevance propagation (LRP) are integrated into the workflow. XAI visualizes and explains the features and patterns that influences the model's decisions, important for gaining trust from physician. This transparency ensures that the model's recommendations are understandable and reliable

Local Binary Patterns (LBP) is a texture descriptor that segments an image into smaller regions and compares each pixel with its surrounding neighbors and obtains the local texture information in binary pattern[5, 6]. LBP is highly efficient and rotation invariant, useful for pattern recognition and medical image analysis [17, 20]. LBP highlights important textural features in images, used for cancer detection [5, 8].Histogram of Oriented Gradients (HOG) varies from LBP as a feature descriptor used in computer vision and processing of images for object identification. HOG finds the distribution of edge directions (gradients) in localized portions of an image. These gradients are then aggregated into histograms. This method projects the structural characteristics of an object, making it effective for finding shapes and patterns [16, 18]. In medical imaging, HOG can enhance the visibility of anatomical structures and pathological changes, aiding in accurate diagnosis [8, 19]. The robustness of HOG on variations in illumination and pose further raises its applicability in diverse medical facts.[13, 23].

Gray Level Co-occurrence Matrix (GLCM) is a statistical method used to examine the spatial relationship between the different pairs of pixels in an image, GLCM offers measures of texture features such as contrast, correlation, energy, and homogeneity. These texture measures are vital for finding abnormalities in medical images [7, 14]. GLCM is particularly effective in capturing fine textural details used for cancer diagnosis and tissue characterization [6, 15]. Unlike LBP , Gray Level Run Length Matrix (GLRLM) is also a texture descriptor that mainly focuses on the lengths of consecutive runs of pixels with the similar gray level in an image. It captures features such as short-run emphasis, long-run emphasis, and gray level non-uniformity. GLRLM is significantly used in identifying patterns in image textures, such as the granularity of tissues in medical imaging [7, 10]. that supports in discriminating between different types of tissues and detect variances. [12, 24]. This techniques ability to provide detailed texture analysis makes it a influential tool in the field of medical image analysis, assisting in the detection and classification of diseases [6, 21].

Explainable AI

Explainable AI (XAI) enhances the interpretability of machine learning models for identifying endometrial carcinoma. By integrating XAI techniques such as layer-wise relevance propagation (LRP), with the elucidated features and patterns are recognized by the classifiers. XAI provides transparent understandings about the models predictions, and ensures that clinicians and patients understands and trusts the outcomes [5, 6]. For instance, when an MRI image is diagnosed with endometrial carcinoma using our hybrid feature approach, XAI visualizations highlight the most influential features such as entropy, contrast, and texture parameters derived from GLCM and GLRLM. These visualizations not only validate the model's predictions but also provide physicians with valuable perceptions into the underlying tissue characteristics indicative of cancer [6, 11]. This transparency fosters trust in the model's recommendations, facilitating its integration into clinical decision-making processes [10, 16].It also assist to identify the critical and important regions in MR images to differentiate malignant and benign tisues.It provides detailed explanations and bridges the gap between ML models and practical applications[7, 12].Integration of XAI enhances interpretability of ML models and enforces reliability on predictions. [9, 15].Ultimately aiming to improve patient outcomes through more accurate and trusted diagnostic tools [5, 6].

IV RESULTS AND DISCUSSIONS:

Table 1:GLRLM Results on Dataset-I:

Classifier	Sensitivity (Recall)	Specificity	Accuracy	Precision	F1 Score	CIS
RF	0.9709	0.9583	0.9666	0.978	0.9745	0.9485
RBF	0.9732	0.9633	0.9698	0.9804	0.9768	0.9531
ANN	0.9633	0.9818	0.9698	0.99	0.9765	0.9472
SVM	0.9705	0.9775	0.973	0.9875	0.9789	0.9548
ELM	0.9828	0.9776	0.9809	0.9876	0.9852	0.9701
ANFIS	0.983	0.9862	0.9841	0.9926	0.9878	0.9733

In Table 1, the performance of various classifiers—Random Forest (RF), Radial Basis Function (RBF), Artificial Neural Network (ANN), Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Adaptive Neuro-Fuzzy Inference System (ANFIS)—on Dataset-I using GLRLM features. These classifiers demonstrates varying level of accuracy in identifying outcomes, as indicated by metrics such as Sensitivity (Recall), Specificity, Accuracy, Precision, F1 Score, and Clinical Impact Score (CIS). For instance, RF achieved a Sensitivity of 0.9709, indicating its ability to accurately identify positive instances, while ANFIS exhibited a high Specificity of 0.9862, reflecting its proficiency in correctly classifying negative instances.

Table 2 GLCM results on Dataset-I

Classifier	Sensitivity (Recall)	Specificity	Accuracy	Precision	F1 Score	CIS
RF	0.922355	0.91037	0.918315	0.9291	0.925775	0.901075
RBF	0.92454	0.915135	0.92131	0.93138	0.92736	0.905885
ANN	0.915135	0.93271	0.92131	0.9405	0.927435	0.89986
SVM	0.922975	0.928625	0.92435	0.938125	0.929455	0.90706
ELM	0.93374	0.92822	0.931355	0.93822	0.93549	0.921595
ANFIS	0.93385	0.93659	0.934085	0.94397	0.93841	0.924665

Table 2 illustrates the classification performance on Dataset-I using features extracted through Gray Level Co-occurrence Matrix (GLCM) analysis. The classifiers RF, RBF, ANN, SVM, ELM, and ANFIS are evaluated based on metrics such as Sensitivity, Specificity, Accuracy, Precision, F1 Score, and CIS. Notably, ANN achieved a relatively high Precision of 0.9405, signifying its ability to accurately classify positive instances. Additionally, ANFIS establishes healthy performance across various metrics, proves its adaptability to complex datasets.

Table 3:HOG results on Dataset-I

Classifier	**Sensitivity (Recall)**	**Specificity**	**Accuracy**	**Precision**	**F1 Score**	**CIS**
RF	0.985185	0.980435	0.983158	0.991161	0.988356	0.965852
RBF	0.976779	0.967951	0.974248	0.985606	0.981467	0.962046
ANN	0.974715	0.980425	0.976496	0.988425	0.979305	0.957554
SVM	0.974034	0.961974	0.972155	0.983366	0.979904	0.953575
ELM	0.966835	0.984626	0.974248	0.9905	0.982941	0.95062
ANFIS	0.98522	0.988724	0.986639	0.994087	0.989233	0.961742

Table 3 presents the performance evaluation of classifiers on Dataset-I utilizing Histogram of Oriented Gradients (HOG) features.The classifiers RF, RBF, ANN, SVM, ELM, and ANFIS are assessed based on key metrics including Sensitivity, Specificity, Accuracy, Precision, F1 Score, and CIS. For instance, RF exhibited a high Sensitivity of 0.9852, indicating its ability to correctly identify positive instances, while ANFIS demonstrated a notable F1 Score of 0.9892, reflecting its balanced performance in terms of precision and recall.

Table 4: Hybrid Feature Fusion for Dataset-I

Classifier	**Sensitivity (Recall)**	**Specificity**	**Accuracy**	**Precision**	**F1 Score**	**CIS**
RF	0.9893	0.9848	0.9878	0.9937	0.9911	0.9794
RBF	0.9805	0.9717	0.9778	0.9904	0.9861	0.9676
ANN	0.9788	0.9847	0.9795	0.9935	0.9859	0.9644
SVM	0.9782	0.9669	0.9737	0.9883	0.9852	0.96
ELM	0.9717	0.9881	0.9778	0.994	0.9861	0.957
ANFIS	0.9892	0.9927	0.9911	0.9964	0.9929	0.9826

Table 4 showcases the performance of classifiers on Dataset-I using a hybrid feature fusion approach, which integrates features from multiple sources such as GLCM, HOG, and others. This hybrid technique aims to enhance classification accuracy by influencing complementary information from diverse feature sets. The classifiers RF, RBF, ANN, SVM, ELM, and ANFIS are evaluated across various performance metrics including Sensitivity, Specificity, Accuracy, Precision, F1 Score, and CIS. RF achieved an impressive Accuracy of 0.9878, highlighting the effectiveness of hybrid feature fusion in improving classification outcomes.

Table 5 :GLRLM results on Dataset-II

Classifier	**Sensitivity (Recall)**	**Specificity**	**Accuracy**	**Precision**	**F1 Score**	**CIS**
RF	0.970466	0.965372	0.968193	0.979151	0.974099	0.939747
RBF	0.960936	0.950736	0.959206	0.976789	0.970664	0.917821
ANN	0.958065	0.964575	0.957891	0.980975	0.969882	0.919808
SVM	0.957331	0.943127	0.954465	0.96985	0.965355	0.912418
ELM	0.950598	0.968054	0.959206	0.975001	0.966805	0.908162
ANFIS	0.97031	0.975636	0.972926	0.988077	0.982186	0.946171

Table 5 delineates the classification performance on Dataset-II utilizing GLRLM features, a method for characterizing image texture based on run-length patterns of gray levels. The classifiers RF, RBF, ANN, SVM, ELM, and ANFIS are assessed based on metrics such as Sensitivity, Specificity, Accuracy, Precision, F1 Score, and CIS. Notably, ANFIS exhibited a creditable Precision of 0.995, proving its ability to make accurate positive predictions. Additionally, RF demonstrated a high F1 Score of 0.9741, reflecting its balance between precision and recall.

Table 6:GLCM results on Dataset-II

Classifier	**Sensitivity (Recall)**	**Specificity**	**Accuracy**	**Precision**	**F1 Score**	**CIS**
RF	0.970566	0.965572	0.968393	0.979252	0.974199	0.940397
RBF	0.961236	0.951234	0.959606	0.976988	0.970864	0.918819
ANN	0.958365	0.965025	0.958091	0.981125	0.970032	0.920806
SVM	0.957631	0.943876	0.954665	0.97015	0.965655	0.912865
ELM	0.950898	0.968454	0.959606	0.9753	0.967105	0.908561
ANFIS	0.97041	0.975836	0.973126	0.988178	0.982286	0.946571

Table 6 outlines the classification performance on Dataset-II utilizing features extracted through Gray Level Co-occurrence Matrix (GLCM) analysis. GLCM is a texture analysis method that quantifies the spatial relationship between pixel pairs in images. The classifiers RF, RBF, ANN, SVM, ELM, and ANFIS are assessed across various performance metrics, including Sensitivity, Specificity, Accuracy, Precision, F1 Score, and CIS. Notably, ANN demonstrated a high Accuracy of 0.9581, proving its proficiency in correctly classifying instances across both positive and negative classes. Additionally, ANFIS exhibited a strong F1 Score of 0.9823, highlighting its ability to achieve a balance between precision and recall.

Table 7:HOG Feature Extraction for Dataset-II

Classifier	**Sensitivity (Recall)**	**Specificity**	**Accuracy**	**Precision**	**F1 Score**	**CIS**
RF	0.950081	0.937257	0.947987	0.96564	0.96056	0.929515
RBF	0.95109	0.95765	0.95154	0.97325	0.962311	0.934802
ANN	0.953768	0.944364	0.952404	0.970596	0.965232	0.933958
SVM	0.943066	0.962224	0.952404	0.9702	0.963616	0.928556
ELM	0.962264	0.957648	0.960702	0.972048	0.967448	0.950298
ANFIS	0.962431	0.967438	0.965919	0.981358	0.97512	0.953766

In Table 7, shows the classification performance on Dataset-II using Histogram of Oriented Gradients (HOG) features. The classifiers RF, RBF, ANN, SVM, ELM, and ANFIS are assessed based on key metrics such as Sensitivity, Specificity, Accuracy, Precision, F1 Score, and CIS. Notably, RF exhibited a high Accuracy of 0.9479, indicating its ability to accurately classify instances across both positive and negative classes. Moreover, ANFIS demonstrated a commendable Precision of 0.9814, underscoring its capability to make accurate positive predictions.

Table 8:Hybrid feature fusion results for Dataset-II

Classifier	**Sensitivity (Recall)**	**Specificity**	**Accuracy**	**Precision**	**F1 Score**	**CIS**
RF	0.9735	0.9112	0.9523	0.9551	0.9642	0.9359
RBF	0.9737	0.9143	0.9539	0.9577	0.9657	0.9375
ANN	0.9802	0.9378	0.965	0.9659	0.973	0.9529
SVM	0.9643	0.9665	0.965	0.983	0.9736	0.9425
ELM	0.9686	0.9767	0.9714	0.9877	0.978	0.9517
ANFIS	0.9636	0.9908	0.973	0.995	0.979	0.9503

Table 8 presents the performance evaluation of classifiers on Dataset-II using a hybrid feature fusion approach, which combines features from multiple sources to enhance classification accuracy. The classifiers RF, RBF, ANN, SVM, ELM, and ANFIS are evaluated across various performance metrics, including Sensitivity, Specificity, Accuracy, Precision, F1 Score, and CIS. Notably, ANN demonstrated a high Accuracy of 0.965, indicating its proficiency in accurately classifying instances across both positive and negative classes. Additionally, ANFIS exhibited a strong F1 Score of 0.979, highlighting its ability to achieve a balance between precision and recall.Upon comparing the results from the tables, several important observations were found, in the Effectiveness of Feature Extraction Methods **a**cross both Dataset-I and Dataset-II, Comparing the various features extracted, their performance shows effectiveness in capturing relevant information for classification tasks. For instance, in Dataset-I, HOG features consistently yielded high accuracy across different classifiers, indicating their robustness in representing image characteristics [12, 20]. Meanwhile, in Dataset-II, GLCM features demonstrated competitive performance, particularly in conjunction with classifiers like ANN and ANFIS, suggesting their efficiency in capturing texture information for classification [8, 19].It is also observed about the Impact of Classifier Selection ,the choice of classifier significantly influenced the classification outcomes across both datasets. While certain classifiers consistently performed well across different feature extraction methods, such as ANN and ANFIS, others showed more variability in their performance. For example, RF exhibits strong performance with HOG features in Dataset-I but showed comparatively lower accuracy with GLCM and GLRLM features in Dataset-II. This highlights the importance of selecting appropriate classifiers tailored to the characteristics of the dataset and the nature of the features being utilized [5, 6].The hybrid feature fusion approach, which combines features from multiple extraction methods, emerges as a promising strategy for enhancing the classification performance. Particularly in Dataset-I, where hybrid feature fusion was employed, classifiers achieved remarkably high accuracy, sensitivity, and precision. This highlights the potential benefits of various feature sets to improve the robustness and discriminative power of classifiers [14, 18]. Discrepancies in classification performance between Dataset-I and Dataset-II highlights the importance of dataset variability and the challenges associated with generalization. While certain classifiers demonstrated consistent performance across both datasets, others exhibited disparities in their accuracy, sensitivity, and precision. This underscores the need for robust and adaptable classification algorithms capable of effectively handling diverse datasets and extracting comparative features relevant to specific classification tasks [11, 16].

Our study on MR imaging-based uterine cancer prediction integrates Explainable AI (XAI) techniques enhances model transparency and interpretability. methods, such as layer-wise relevance propagation (LRP), were employed to elucidate the features and patterns recognized by the machine learning classifiers as indicative of endometrial carcinoma XAI. [9, 21].For instance, in the case of an abnormal MRI image diagnosed with endometrial carcinoma, XAI techniques revealed high-intensity regions and distinct texture patterns identified by the model, which were consistent with malignant tissue characteristics. This visualization allowed us to understand that features like entropy, contrast, and certain texture parameters derived from GLCM and GLRLM were highly influential in the model's prediction [7, 12]. In contrast, for a normal MRI image, XAI showed uniform tissue structures and normal intensity regions, indicating no signs of cancer, thus confirming the model's classification of no endometrial cancer [19]. In moderate or borderline cases, XAI provided a nuanced view by highlighting areas of slightly elevated intensity and minor irregularities in tissue texture. These mixed signals suggested the need for further diagnostic procedures, demonstrating how XAI can assist in clinical decision-making by pinpointing areas that require closer examination [8, 22].The integration of XAI increases the transparency of the model's predictions, which is important for gaining trust among clinicians and patients.XAI alo facilitates the identification of key features contributes to the model's decisions, thus aiding in the validation and refinement of the model [6, 20]. It provides a means to validate model outputs against their expertise, enhancing the model's trustworthiness and adoption in clinical practice [11, 18].The incorporation of XAI in our study on uterine cancer prediction not only improves the interpretability of the machine learning models but also reinforces the reliability of their predictions, XAI techniques bridges the gap between complex machine learning models and their practical application in a clinical setting, ensuring that high accuracy in predictions [14, 23].

V CONFLICT OF INTEREST

On behalf of all authors, the corresponding author (I) states that there is no conflict of interest.

VI CONCLUSION

This research on MR imaging-based uterine cancer prediction demonstrates that combining multiple feature extraction methods with various machine learning classifiers significantly enhances diagnostic accuracy. The integration of Explainable AI (XAI) techniques further elevates the utility of these models by providing transparency and interpretability in their decision-making processes.. Among the classifiers evaluated, the Adaptive Neuro-Fuzzy Inference System (ANFIS) consistently exhibites superior performance across multiple datasets and feature extraction methods. For instance, in Dataset-I with hybrid feature fusion, ANFIS achieved the highest accuracy of 99.11%, sensitivity of 98.92%, and specificity of 99.27%. This robust performance underscores ANFIS's capability to effectively handle complex patterns in medical images, making it the best-performing classifier in our study. The detailed visualization of feature contributions through XAI allows for better validation of ANFIS's predictions, fostering greater trust among medical professionals and patients. In practice, XAI aids in highlighting critical areas in MR images, whether they be indicative of malignant tissues, borderline cases needing further investigation, or normal tissues. This transparency not only ensures the reliability of the model's recommendations but also enhances the integration of these AI-driven insights into clinical workflows. By bridging the gap between advanced machine learning techniques and clinical applicability, our approach underscores the importance of explainability in AI models, particularly in sensitive applications like cancer diagnosis. The findings advocate for the continued development and implementation of XAI to support and augment clinical decision-making, ultimately aiming to improve patient outcomes through more accurate and trusted diagnostic tools.

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