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Image processing and machine learning approaches for the automatic diagnosis of endometrial cancer: A comprehensive review

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***Abstract*---**In many medical imaging based diagnosis, Deep Learning (DL) algorithms play an essential role. A DL algorithm can be used to identify abnormal and normal cells in the uterus's endometrium in order to discover Endometrial Cancer (EC) cells. EC is difficult to diagnose since it develops without causing any symptoms. DL algorithm can distinguish between normal, abnormal, and malignant cells, producing more accurate findings than screening by hand procedures such as liquid cytology and Pap smear test. For the accurate and easier detection of EC cells, DL employs multiple architectures. The findings of an analysis and survey of the many forms of DL architecture, as well as their accuracy and performance, are addressed in this work. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are the most modalities of advanced imaging used for the non-invasive diagnosis of EC. EC is considered as the fourth most prevalent malignancy in women and one of the common most gynaecological cancers. Diagnostic imaging in clinical evaluation with has not been proven yet to be precise enough to substitute surgical staging in determining the spread of cancer. It may allow for improved surgical process optimization and a more customised therapeutic plan.

***Keywords*---**Endometrial Cancer, Deep Learning, Computed Tomography, Magnetic Resonance Imaging, Clinical Evaluation.

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1. Introduction

Endometrial Cancer (EC) is the type of cancer which is second most frequent among women of all ages. Because there are no signs in the early stages of this malignancy, it is a fatal disease. The Pap smear test is a manual hand screening approach that collects cervical cells from the uterus's cervix area. The cervical cells are manually collected using a brush or spatula by the doctor or physician. The cells from cervix are collected in a sealed container before being transported to a laboratory for categorizing normal and abnormal cells manually. This screening method is only carried out by a few qualified pathologists. However, because of human errors in classification of cells, this approach has a high false positive percentage. This is an extremely cost-effective method, as a pathologist may only classify 4 to 5 slides per day using this method. Due to the uneven boundaries of the nucleus and cytoplasm found in the structure of the cell, the process is challenging to accomplish at a faster rate. The nucleus may be overlapping with the nuclei of multiple cells, making it difficult to determine the limits of a single cell and making classification arduous. The method of liquid cytology based (LCB), which immerses the obtained samples of cell from cervix in a liquid contain in gacetic acid of 5%, is the second most frequent screening method. According to the data from World Health Organization (WHO), 6.5% of cancer occurs in cervix and endometrial area. The statistical distribution of yearly increase in various cancer types across the globe is depicted in Fig.1.

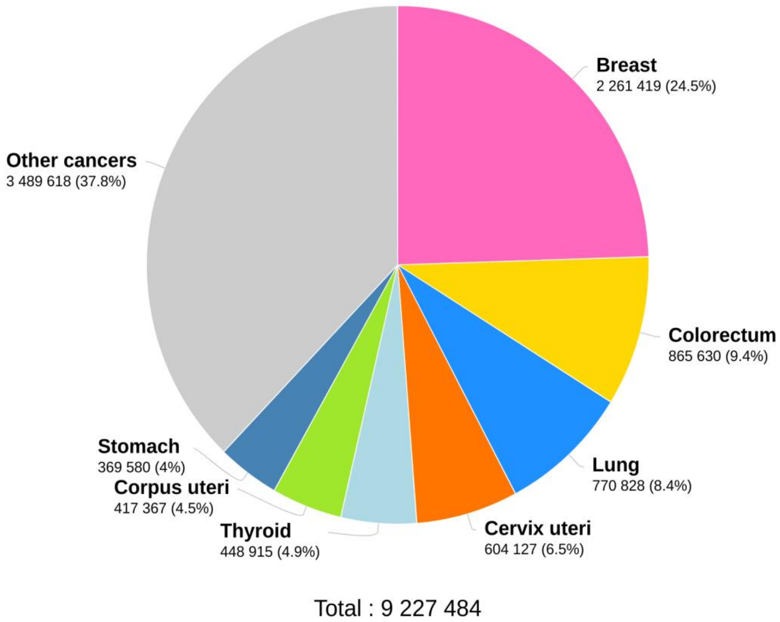
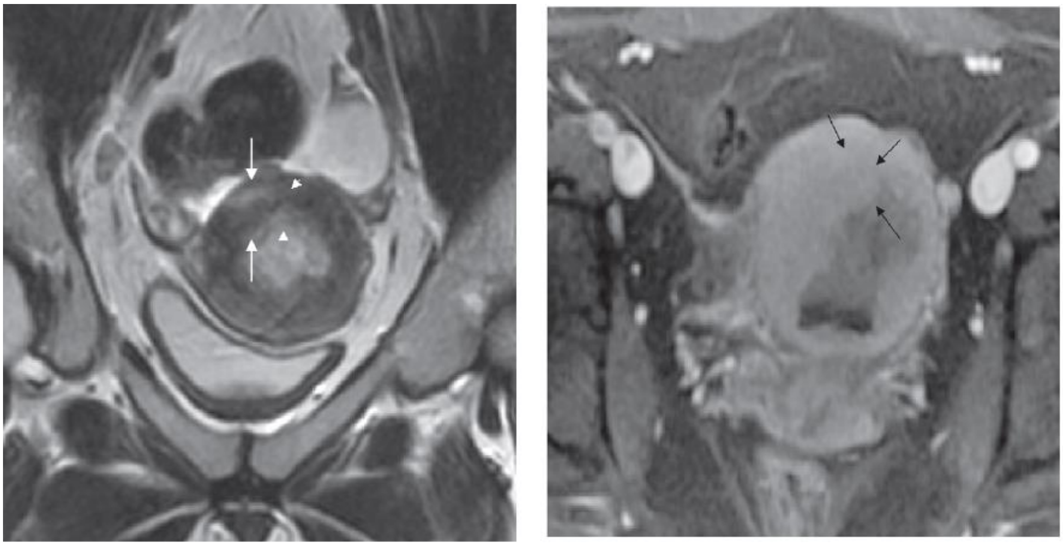


Fig. 1: Statistical distribution of various cancer types

Pelvic Magnetic Resonance Imaging (MRI) is one of the newer approaches to evaluate the extent of the disease. This technique was used for the evaluation of lymph node involvement as well as tumor invasion of the myometrium and cervix and is presently accepted in the EC characterization. For better assessment of EC by the aid of contrast enhanced imaging and diffusion weighted MRI (DW-MRI), female pelvic imaging MRI is being magnified nowadays. MRI is highly useful in providing contrast between soft tissues in the endometrial area. Fig 2 illustrates sample MRI images having EC in different views.



(a) (b)

Fig.2: Endometrial carcinoma spread to the inner myometrium (a) Coronal View, (b) Axial View

For the identification of cancer in endometrial area, the input MRI needs to undergo various image processing steps. The accuracy of these image processing steps depends on the quality of the MRI obtained. Various steps in the detection of EC are pre-processing segmentation feature extraction, classification and analysis. The general block diagram of an EC detection system is illustrated in Fig.3.

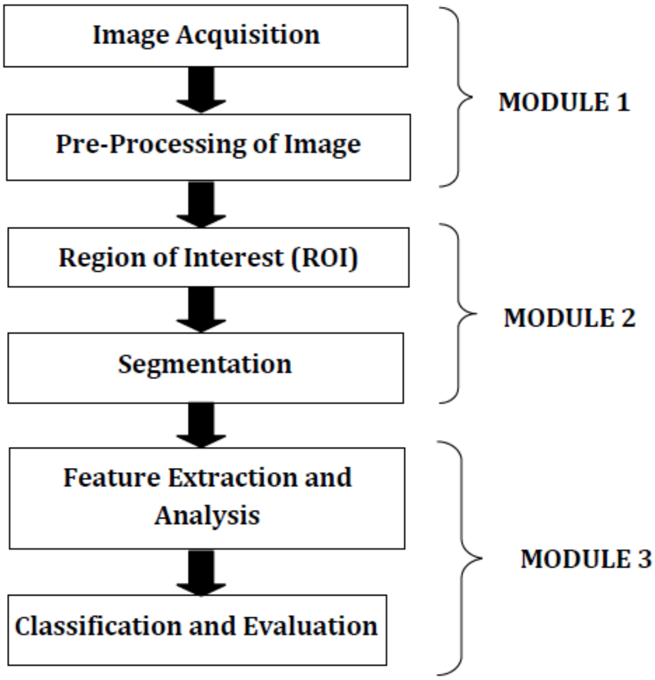


Fig.3: Block Diagram of Endometrial Cancer Detection System

Medical atlases, pathological labs, online portals, and hospitals all provide pictures that are either malignant or benign. The images which are captured have not been processed in any way. PNG, JPG, TIFF, DICOM and other image formats are all acceptable. These images have all been converted to uint8 format. Noise reduction or noise suppression is a pre-processing method. For noise reduction, many filters are utilized, as is common in grey value image processing. Median, Wiener, Gaussian and Mean are some of the filter used. As an intermediary stage, successful biological image analysis typically necessitates acceptable segmentations to locate regions of interest (ROI). The term "segmentation" refers to the division of an image into its constituting areas or objects. When the ROI of the item is found, the segmentation will come to an end. The features of intensity values, such as discontinuities and resemblance, are used in segmentation techniques. Feature extraction is a technique for collecting the visual information of images in order to index and retrieve them. Feature extraction is a term that refers to a portion of data that is useful in completing a complex problem for a certain implementation framework. Each image requires a collection of characteristics after segmentation. Every image is given a feature vector during the feature extraction step, which is utilized to identify and differentiate the image. Topological, morphological and statistical characteristics are examples of features that might be extracted. The characteristics retrieved serve as the foundation for the categorization process. These characteristics are utilized to train the Network and build diagnostic algorithms for detecting EC.

To improve the manual screening process, artificial neural networks are utilised and produce results which are reliable in the detection of cancer in endometrium area. They are simple to use and produce accurate results. The output layer, hidden layer and input layer are the three layers that make up the Deep Learning (DL) architecture. In each layer, the numbers of layers are determined by the input images provided to the neurons that connect each layer. With the neuron structure, there are three layers of connectivity, each with its own set of nodes. The amount of input photos used determines the overall number of layers or nodes in DL algorithm. Depending on the data set that the input layer is using, the input layer processes and links to the hidden levels. Two categories of data sets are there: untrained and trained datasets, which provide accuracy using unsupervised and supervised learning approaches, as well as several types of neural network topologies such as back propagation and feed forward, which employ the different ways of data set. The steps involved in DL approaches for EC detection is depicted in Fig.4.

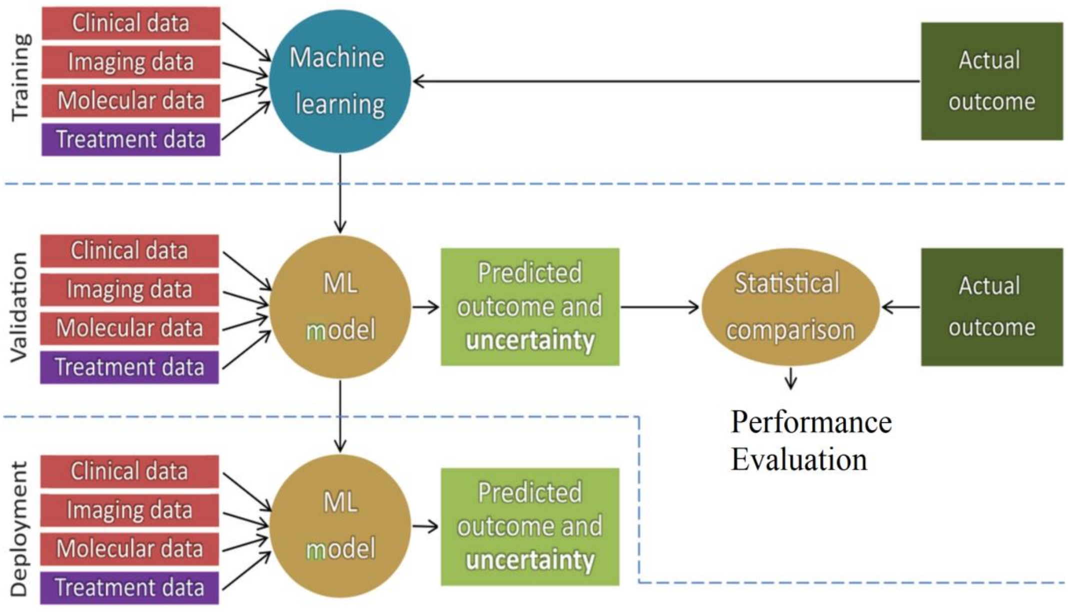


Fig.4: Artificial Intelligent Approach for EC Detection

1.1 Motivation

Artificial Intelligence based image processing approaches plays a significant role in the early detection, monitoring, diagnosis, and treatment of EC. These approaches assist the doctor to make a more accurate disease diagnosis and can achieve high accuracy and even exceed the human recognition ability. After a woman is diagnosed with EC, doctors will try to figure out how much it has spread and this process is called staging. The stage of a cancer describes the spread of cancer within the body. It helps determine how serious the cancer is and how to treat the cancer and determining how successful the treatment might be. The EC is classified into four stages based on how much it has spread. The stage 1 cancer is only present in the uterus. In stage 2, the cancer is present in the uterus and cervix and in stage 3, the cancer has spread outside the uterus, but not as far as the rectum or bladder and might be present within the fallopian tubes, ovaries, vagina, and nearby lymph nodes. The stage 4 cancer has spread beyond the pelvic area. It might be present in the bladder, rectum, and/or distant tissues and organs. MRI is best suited to detect and evaluate EC within the endometrial cavity; tumour infiltration into myometrium, endocervix, and gross extension into the parametria; and other pelvic tumour deposits. Quantitative measurements on MRI have higher diagnostic performance in deep myometrial invasion identification than direct observation by radiologists; sometimes, it is inaccurate to assess some invisible EC lesion on MRI. Rapid development of deep learning techniques, from the earliest shallow CNN model to the deep CNN model and the use of transfer learning, data augmentation and other new techniques motivated to use them in the automatic detection of EC.

1.2 Organization of the Paper

This review paper is arranged in the following manner. Section 1 provides an overview on EC and the imaging methodologies. Section 2 provides a detailed review on the existing methodologies used for the classification and segmentation of EC using deep learning techniques. Section 3 provides a detailed discussion in which comparison between various existing technologies is performed. Section 4 is the concluding section.

2. Existing Methods

Bucinski *et al* [1] used a method to predict EC by using Principal Component Analysis (PCA) and Artificial Neural Networks (ANN) of patients. Patients were observed over a period of 5 years, in which one group survived and the others didn't. It was observed that, the capabilities of ANN with related to prognostic features tested on patients turned out pretty high. And by adding the logic behind PCA, PC1 and PC2, the two components could be extracted and thus in result, could also be accounted for giving a cumulative variance of 23% for the data analysed. A clear cut clustering along with the apparent clustering of the patients were studied. The variables which were dissimilar and similar to each other could be studied, by using this method. DW-MRI was used by Bharwani *et al* [2] in their research of identification of EC. Permissions from patients as well as their family members were taken before hand for obtaining the scans needed. Apparent Diffusion Coefficient (ADC) measurement by utilizing DW-MRI demonstrated that EC can be identified with precision. But by using the ADC value of the tumor, histological grades could not be used, which were in range of 1 to 3. The ADC threshold gave an accuracy of 92.7% during the prediction of EC. However, it could not differentiate between endometrial pathology and EC.

A model for predicting EC was proposed by Xu *et al* [3] by using target detection algorithm. Lymph node assessment is crucial for the identification and curing of prognosis and decisive prediction for EC. Positron Emission Tomography (PET) using radionics technology showed that the sensitivity of staging of lymph nodes could be better improved. PET, however, is not the default model of prediction for EC. By studying the role of MRI and clinical parameters, lymph nodes metastasis can be easily predicted. The training set revealed an AUC of 0.892 and the test set revealed an AUC of 0.884. While algorithm was used in radiomics, 1570 3D features were extracted. These features corresponded to wavelet features, first order statistical features, texture features and morphological features. The model also balanced the sensitivity and specificity and also saves time.

Texture analysis and Support Vector Machine (SVM) were used by Torheim *et al* [4] during their research in dynamic contrast enhanced MRI. Tumor features could be identified with deviations in large standard. The deviation was identified from a cured and relapsed patient. The slices show the variations in Brix parameters, which have higher values for heterogeneous parameters. The distribution of the parameters, is such that there is high and low contrast agent uptakes and washouts. The SVM model based predicted a treatment outcome with stage significantly (p = 0.006) and the clinical features volume. The cross-model validated accuracy was observed at 69%.

3D ultrasound and MRI were used by Christensen *et al* [5] in their research for assessing myometrial invasion in EC. Ten patients were observed in their research and no residual tumour was found in the final hysterectomy. Two of them were found with atypia in resectoscopic samples, while those who had invasive EC were eight. Further, more details could be extracted with their proposed methodology. The results observed from the myonometrial invasion using Deep Learning (DL), the MRI was found better than other imaging modalities. This methodology displayed an accuracy of 84%. Independent Level Sets and multi SVMs were used by Kashyap *et al* [6] in their cervical cancer detection and classification. They collected data from National Cancer Institute (NCI). Only the significant figures were obtained as part of the PCA usage in their study. Bi-plot function and PCA were used to extract the discriminatory features. Sum of Variance, Sum of Squares, Cluster Shade and Cluster Prominence are the principal components which were extracted using the PCA. The confusion matrix was plotted with by feeding these values to different types of Multi SVMs. As a result, the polynomial classifier was found to provide with great results with an accuracy of 95%.

EC can be detected and classified using texture analysis scheme proposed by Sneha *et al* [7]. They derived features from the MR images, which belonged to patients who were going through advanced EC. These features would be then used to predict the staging of the disease. Transform features and second order textures of the tumors were used to construct the non-linear SVM classification. Transform features were mainly energy based which were used for predicting the output. The second order features were used to predict the treatment outcomes, from MR images pre-treated with CT. The models based on transform method had accuracy percentages for axial T- weighted MRI around 81% and 82%for T2-weighted MRI. It is possible to observe that the transform feature is outperformed by the texture feature for accurate tumor prediction.

MRI analysis based on multi-resolution wavelet for the detection of Cervical Cancer (CC) was introduced by Roy *et al* [8]. Medical images can have quality limitations, addition of noise elements, machine and human related errors. MRI, which are statistically analysed through computing environment, cannot only save time, but also can provide more accurate decisions. While magnifying the processed images, the calculations are computed through pixels. This can magnify the amount of data processed through the output, and the analysis of such a date can be more accurate and classifications can be done more precisely. While considering this method for CC analysis, the precision was found out to be 98.8%. Devi *et al* [9] proposed an ANN based classification method for CC detection. Due to its accuracy and discrete applications, an important role is played by ANN in many healthcare industry applications. By integrating multiple neural algorithms, the efficiency of the Neural Network (NN) architecture can be increased tremendously. The normal and abnormal cells are classified, which are connected to a secure web like algorithm, which in turn identifies CC. Through this method, CC can be identified earlier, even before there is any emergency. There are different kinds of AI detections methods used in the field of healthcare, most of them focused on the area of cancer detection. Shrivastava *et al* [10] proposed a method to detect EC through MRI even at a pre-operative stage using retrospective analysis. Their studied revealed the different roles pre-operative staging played in EC analysing. Compared to previous studies, their results gave a better accuracy of 88%.

Bourgioti *et al* [11] proposed that EC can be identified on MRI through predictive algorithms. Their model proposed tumor as an independent predictive factor for both pelvic metastatic lymph adenopathy presence and myometrial invasion. This model provided sensitivity of 78%, specificity of 92.7% SP and Positive Prediction Value of 90.5%. They focused on the application of largest diameter of a single-tumor, for a high risk patient. While using diameter, the study still shows that the output generated is still competitive. A random forest based CC diagnosis method was put forward by Sun *et al* [12]. Their system provided an accuracy of 90.58% while using the Fuzzy C-Means (FCM) model integrated with Herlev data set. The system however used only the nucleus feature, rather than all features and provides a better classification model. It should also be noted that, a classification model can provide better accuracies which incorporates 12-15 features. The cytoplasm features are also included rather the nucleus alone. Nucleus features based system can give a better performance, but there are not a lot of good systems which can outperform higher numbers.

Data-driven diagnosis using machine-based approaches for CC detection was provided by Wu *et al* [13]. Their classification results, gave an accuracy of 90.48% which outshines many previous methods. For the classification of CC dataset, three SVM-based approaches are applied and the results were reviewed. Both benign cancer and malignant cancer can be classified by using the standard SVM method. Classification is easily done by using SVM-PCA, as it has the ability to restrict the number of features to a range of 8 from 30, which is even greater than the normal SVM.A preliminary analysis for preoperative risk of texture model based on MR imaging was done by Ueno *et al* [14]. They used mathematical expressions and models which were integrated on the MR imaging texture features. While taking data from independent data set, it should be validated; hence caution should be considered while observing results. The model demonstrated more accurate diagnostic values while assessing Deep Myometrial Invasion (DMI). The study is not yet completed and more research is needed, to refine and standardize the actual applications of clinical decision making. Qualitative diagnostic accuracy for DMI was found to be 81%.

Motion MRI was used by Thapa *et al* [15] to identify CC cells. They observed the different parameters to find the feasibility of implementing analysis ofa histogram for detection of perfusion and diffusion patterns of myometrium, CC and gluteus maximums. This method helps in identification on CC cells during early stages, and plays an important role in differentiating tissues. It independent and robust factors were observed to identify the stages of CC with 0.856 AUC, specificity of 79% and sensitivity at 87%. A machine learning prediction method was used by Gunakan *et al* [16] for the prediction of the existence of lymph node involvement in EC. In the LNI analysis, histopathological results were used. By using the Naive Bayes algorithm, they improved the existing models by using a different technique. The data can be used at any point of time with this algorithm hence it do not need assumptions. By evaluating these models, real time predictions could be made. The Naive Bayes machine learning algorithm seems to provide accuracy in ranges from 84.2 % to 97.6% for different models. Bonatti *et al* [17] used MRI in their model for histological grade prediction of EC. The system provided an efficiency of 91%, which indicates that the study can develop a product which can be used as a machine for the study and analysis of EC and the depth of myometrial infiltration. It was seen that high-grade neoplasms are a cause for the myometrial infiltrations with thickness level greater than 50%.

Classification of EC using preoperative MRI was proposed by Lavaud *et al* [18] as they are one of the mostly used in healthcare industry. The system was able to predict a recurrence from high risk underestimation from 28.8% to 15.3%. This system had many limitations and it was a small study of retrospection. The system provided a preoperative underestimation of 29%. Alyafeai *et al* [19] proposed a CC classification by utilizing fully-automated DL pipeline. Cervigram image was used to extract the Pyramid Histogram of Oriented Gradients (PHOG) and the image gradient stores the edge information hidden within the image. This method provided a Jaccard Index of 0.82 and AUC of 0.68. Goel *et al* [20] evaluated EC by predicting the accuracy of MRI. While identifying the different objects in the study, the MRI was found to be sensitive and specific while compared to traditional methods. There are different papers which predict the sensitivity and other indicators of the method.

Convolutional Neural Network (CNN) based segmentation of MRI images was proposed by Kurata *et al* [21]. Different loses were incorporated and tested out, but in the end decided to adopt the 8 layer in their final model. The dice model was selected after up sampling and down sampling with the least loss to 8. The dice loss for the original U-net was 0.295 compared with 0.180 obtained from this result. The dice value obtained for the proposed method was 0.82. Extreme Learning Machines (ELM) and CCN were used by Ghoneim *et al* [22] for the classification of CC. The classifier model was integrated on top of the CNN deep system embedded on Herlev database. The model provided never before seen accuracies. In the 2-class problem, 99.7% accuracy was achieved by the ELM-based classifier while it achieved 97.2% in the 7-class problem. Diffusion Weighted Imaging (DWI) integrated with Diffusion Kurtosis Imaging (DKI) was used by Yue *et al* [23] for evaluating the histological features of EC. Compared with traditional DWI methods, the non-Gaussian model of DKI has shown superior advantages while predicting EC results. The system provided an accuracy of 96.7%.

For the assessment of EC, Chen *et al* [24] developed a dual-stage automated DL approach on the basis of a CNN. The main goal of this analysis is to investigate the distinguished performance of DL model in evaluating myometrial invasion (MI) depth using T2WI–based MRI. The lesion area was determined using T2WI-based MR images of both sagittal and coronal manner. To find the lesion region on ECM, training was done on the detection model based on the YOLO v3 method. The discovered areas were then sent into a DL network based classification model to automatically determine MI depth. The accuracy of the classification model was 84.78 %, with a specificity of 87.50 % and a sensitivity of 66.67 %. Hodneland *et al* [25] used CNN in EC patients to automate tumor segmentation, allowing textural and volumetric properties of tumours to be extracted automatically. Based on preoperative pelvic imaging, the network was processed, verified, and tested on a sample of 139 EC patients in total. The system was able to obtain tumor volumes at a level that was equivalent to that of a human expert. The CNN was also capable to create a set of segmentation masks with human expertise that was comparable to human expert agreement of inter-rater. The dice value obtained using this approach was 0.96. This method of automated tumor profiling appears to be a promising way for improved prognostication and individualization of therapy strategies in EC.

Another MRI based approach was taken by Xu *et al* [26] for pre-operative prediction of EC. The proposed system used radomics features predictive models for the detection of EC. This system provided accuracy value of 83% as a result of incorporating the small LN size and relative ADC. Gil *et al* [27] incorporated DWI for the assessment of EC. This method analysed demographic characteristics and histological findings for post operation. The study was conducted on a group of patient to identify the percentage of patients with different diagnosis. 57% of the patients were found of having Superficial Myometrial Invasion (SMI), and the rest 43% had DMI. Algorithms of transfer learning and ensemble learning techniques were used by Xue *et al* [28] for EC classification. By observing the accuracy curve of training and test data, the VGG-16 and Resnet-50 were found to be more stable. The system also provided high accurate EL and TL for thee histogram. The accuracy was found at 66% for AQP staining while it was 75% for HIF staining.

Lin *et al* [29] developed fully automated tumor segmentation by using DL and also designed extraction of CC from MRI radiomics features. The easiness of extracting ADC radiomics features was studied by exploiting a fully automated deep neural network based segmentation of DWMR. The system gave a dice value of 0.70 and demonstrated double the improvements compared to previously suggested automated classification and segmentation machines. Without manual interference, standard DICOM images can be automated for segmentation by following a U-Net architecture of a FCNN. DL was incorporated on single T2-weighted image by Urushibara *et al* [31] for diagnosing CC. For Deep CNN (DCNN), contouring time for one patient was 15 seconds. The DCNN model provided accuracy of 90.8%, specificity of 93.3% and sensitivity of 88.3%.

Based on the CNN, Zhang *et al* [32] examined an intelligent identification of EC using MRI. A total of 158 patients with EC participated in the research, which was branched into two groups: testing and training. The EC prediction's imaging model was built in accordance with the features based on the CNN. Clinical data and imaging factors were used to create a complete prediction model. According to the results, this model's area under curve (AUC) was 0.897. The certainty of the prediction was high; indicating that radiomics characteristics might be used as non-invasive indicators for EC prediction. Internet of health things was incorporated by Khamparia *et al* [33] in their DL system for detection and classification of CC. To keep the life quality of a patient, the prognosis and uterine adenocarcinoma needs to be distinguished. Enhanced MRI was used to differentiate normal and cancerous region. 97.89% accuracy was provided while using random forest along with ResNet50. This method can be used to diagnose many other conditions as well.

An ensemble approach for CC detection using machine learning was incorporated by Lu *et al* [34]. The proposed an integration of a gene sequence module into an efficient auxiliary model. The system provided an accuracy of 83.16%. The method suggested that machine learning had hidden capabilities in the field of healthcare sector. Colposcopy images could also be incorporated as an added advantage. The system also gave a high F1-score of 32.80%. DL was integrated into MRI to predict CC in the early stages by Jiang *et al* [35]. Multi-parametric MRI data was used to differentiate non-vessel invasion from vessel invasion in CC. in early stages, DNN based radiomics are found more useful as prediction tools without manual interruptions. This system is found to give AUC value of 0.911, Specificity 75.2% and sensitivity of 88.1%.

Multiple mathematical models were analysed by Zhang *et al* [36] for EC detection and prediction. Before surgery, prognosis related risk can be reduced, by studying the comprehensive information of tissue properties. To support clinical implementations and selections, the research provided high inter-observer agreement. This method provided AUC of 0.825. MRI was used to identify EC by Li *et al* [37]. APT values of normal tissues were compared with those against those of benign lesions and malignant tumours. Good image quality was provided in the small area of 20.4mm^2 by lesions. A group of patents were selected and detection of the CC cell was performed. The patients could be easily classified and allocated in reports accordingly based on the test and train data. This method provided AUC of 0.91%, specificity of 86.4%and sensitivity of 83.3%.

MRI based radiomic analysis was incorporated by Bereby *et al* [38]. Tumor grade and LVSI present in the EC was detected by using the texture analysis based on MRI. Tumour short axis measurement gave a better performance when compared to texture analysis. The discordance was observed at 28.8% which was taken between final histopathological findings and preoperative findings. However, for perfect prediction, preoperative endometrial sampling cannot be considered as perfect, and hence the risk can be avoided by analysis of potential recurrences. This system provided AUC of 0.86, specificity of 75%and sensitivity of 95% for the analysis of high-grade tumor. Khoulqi *et al* [39] followed traditional ways of segmentation and classification of CC. This work proposed results with high accurate values of segmentations and classifications. The survival chances can be increased if the system was incorporated to detect CC at early stages by studying the data of MRI images of cervix. Dice result obtained was 0.8414 and it showed that the system has high efficiency in segmentation and classification of pelvic MRI images.

Deep CNN was used by Dharani *et al* [40] for the visualization of CC. Both single cell and multi cell images were considered for the screening of CC. A mask R-CNN was used for segmentation, while an algorithm incorporating simple nuclei detection for multi cells was used for detection. An overall F-score of 90%, precision 92% and recall of 91% was provided by the system, with features available in both single and multi-cell images.EC prediction using DL and intelligent recognition was performed by Zhang *et al* [41]. The EC prediction model was designed for preoperative analysis of the pelvic cavity. After analysing the data from different test groups, it is found that it can be used in clinical applications. The AUC value obtained for this method is 0.913. Xu *et al* [42] proposed a radomics detection model for EC. The accuracy was found to be 82.1% and specificity of 84.7%. This model provided better diagnostic performance in clinical roles, by providing superior predictive algorithms.

To overcome the data imbalance problem, Zheng *et al* [43] proposed a profound understanding strategy based EC classifier based on data augmentation was employed in the classifier training. The accuracy of model test for axial DWI pictures is 0.870, and the AUC is 0.8611 in actual data and 0.9764 in enhanced data, according to the experimental results. On MRI images, the deep learning EC classifier has the potential to be used in computer-based diagnosis for EC. For a computer-aided analysis of EC detection a practical technique is to be implemented to use a CNN classifier for EC. Bnouni *et al* [44] proposed that CNN can be boosted by ensemble image pre-processing methods and CC can be segmented. The proposed boosting strategy is a fully automated novel ensemble pre-processing for CC segmentation. The segmentation accuracy was found to be 76.8% which was promising. The DICE coefficient was up to 0.741 while using conventional CNN and 0.768 while using paralleled CNN.

CC classification using ML algorithm was proposed by Arora *et al* [45]. While comparing the four different classifiers available, the polynomial SVM classifier outshines with a high accuracy of 95%, while compared with linear, quadratic and polynomial classifiers. 3 out of 20 test images were misclassified for RBF SVM and 3 by quadratic SVM. As the study was restricted by funding and architecture, there are future enhancements which can be made. A DL model was proposed by Zhang *et al* [46] for CC classifications. For diagnostic image classification, CAD was utilized to develop the CNN which was first of its kind. The different types of endometrial lesion images could be easily identified and compared by using the VGGNet-16 model. In five category classification, the system provided accuracy of 80.8% and in two category classification, 90.8% accuracy was provided. The method has potential clinical applications and it can provide objective diagnostic reports. Texture analysis was utilized by Jyothi *et al* [47] for detecting and classifying CC. A method to method detection was introduced to identify cancer cells using ML algorithm. Then the images would be trained with normal and abnormal cells for classification. The reverberation images of MRI of CC are considered in this method to develop and enhance divergence in segmentation. The GLCM provided an accuracy of 70% while the SVM provided an accuracy of 86%.

Hidden myometrial invasion detection using multi-feature fusion and probabilistic SVM was done by Zhu *et al* [48]. SVM provided a high F1-Score of 79.1% over a dataset which had a positive to negative sample ratio of 1:3. Better classification performance was achieved by SVM with single feature than the SVM listed with selected texture features. The class imbalance was addressed by SVM in this method which makes it clinically suitable. Kurata *et al* [49] used a CNN to do automated EC segmentation using MRI. The impact of the picture put into the sequence and size of the batch on segmentation accuracy was studied. 180 patients with EC were utilized to train the updated U-net model out of 200 patients with EC. The segmentation robustness and performance of autonomously derived radiomics characteristics were tested on 20 patients. Improved segmentation accuracy was achieved by using sequence of multiple pictures and a bigger batch size. For the test set, the model's mean Dice, positive predictive value, and sensitivity were 0.806, 0.834 and 0.816, respectively. This model was capable of reliably segmenting EC on MRI and extracting radiomics characteristics.

Supervised learning-based cancer detection was performed by Sikder*et al* [50]. The limitations of MRI and histopathology images were overrun by using individual cancer detection system. The author proposes a practical method to automate cancer detection by incorporating machine learning algorithm. Using a CNN classifier, the training time was reduced and the segmentation accuracy was increased. The system returned an average accuracy of 93%. Matsuura *et al* [51] proposed a MRI for identifying malignant mesenchymal tumors of the uterus. Predictive values of tumors were computed using variant discriminant analysis. The system provided an accuracy of 81.8% making it clinically approvable.

3. Discussion

MRI is specific and sensitive in depicting important EC prognostic factors such as depth of cervical invasion, presence of lymph node metastases, and myometrial invasion which are critical for accurate pre-operative staging, which supports treatment planning and improves overall patient survival. In comparison to endo-vaginal ultrasound and Computed Tomography, MRI has been found to be the best imaging modality for disease progression and treatment management. The goal of this research is to assess the function of Artificial Intelligence (AI) in the diagnosis of EC using MRI. This research was done employing articles gathered from a variety of internet sources, and numerous AI-based approaches yielded high accuracy results. Improved morphologic imaging, depth of myometrial invasion, and overall classification accuracy obtained through a combination of T2, contrast enhanced, and DW-MRI. Post-contrast enhanced images are extremely beneficial for determining the tumor's depth. In comparison to the significantly increased normal endometrium, EC displayed very mild contrast enhancement. Accuracy can be described as the measure of correctly classified MRI images. It is computed by obtaining the ratio of total number of correct classifications of EC to the total number of MRI images.

In order to calculate accuracy the following parameters are required.
True Positive (TP) = An instance of positive classification or correct classification.
False Positive (FP) = An instance in which an image is correctly classified as negative.

True Negative (TN) = An instance in which an image is correctly classified as negative.
False negative (FN) = A positive instance misclassified as negative.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Sensitivity represents the positive cases that are identified correctly. It is the ratio of TP cases to the total images classified as positive. Sensitivity is the measure of MRI images that are correctly classified as EC by the algorithm.

$$Sensitivity = \frac{TP}{TP + FP} \quad (2)$$

Specificity is the ratio of True Negative cases to the total number of negative cases. It is also known as True Negative Rate.

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

Table 1 lists state-of-the-art strategies for detecting EC from MRI. Fig. 5 shows a comparison of different strategies in terms of accuracy.

Table 1: Performance of state-of-the-art strategies for detecting EC

Author	Year	Methodology	*Performance metrics*
Bharwani et al [2]	2011	ADC with DW-MRI	Accuracy : 92.7% Sensitivity :87% Specificity : 100%
Kashyap *et al* [6]	2016	Independent Level Sets and multi SVMs	Accuracy : 95%
Roy *et al* [8]	2016	Multi-resolution wavelet	Accuracy : 98.8% F-measure : 98.8%
Shrivastava *et al* [10]	2016	Retrospective analysis of MRI at a pre-operative stage	Accuracy : 88% Sensitivity : 83% Specificity : 90%
Sun *et al* [12]	2017	FCM model integrated with Herlev Data Set	Accuracy : 94.44% AUC value: 0.9804
Wu *et al* [13]	2017	SVM-PCA method	Accuracy : 90.48% Sensitivity : 100% Specificity : 88%
Ghoneim *et al* [22]	2020	ELM and CCN	Accuracy : 99.7%
Yue *et al* [23]	2019	Non-Gaussian model of DKI	Sensitivity : 96.7% Specificity : 82% AUC value : 0.93
Chen et al [24]	2020	Dual Stage CNN	Accuracy : 90.48% Sensitivity : 100% Specificity : 88%
Urushibara *et al* [31]		DCNN	Accuracy : 84.78%

	2021		Sensitivity : 66.67% Specificity : 87.50%
Zhang *et al* [32]	2021	CNN	AUC: 0.897
Khamparia *et al* [33]	2020	Random forest with ResNet50	Accuracy : 97.89% Precision : 97% Recall : 96%
Dharani *et al* [40]	2020	Mask R-CNN	Accuracy : 99.3% Precision : 92% Recall : 91%
Zheng et al [43]	2021	Deep CNN	Accuracy : 87%
Arora *et al* [45]	2021	CC classification using ML algorithm	Accuracy : 95%
Jyothi *et al* [47]	2021	Texture analysis with SVM	Accuracy : 86%
Sikder *et al* [50]	2021	Supervised learning incorporating machine learning algorithm	Accuracy : 93%

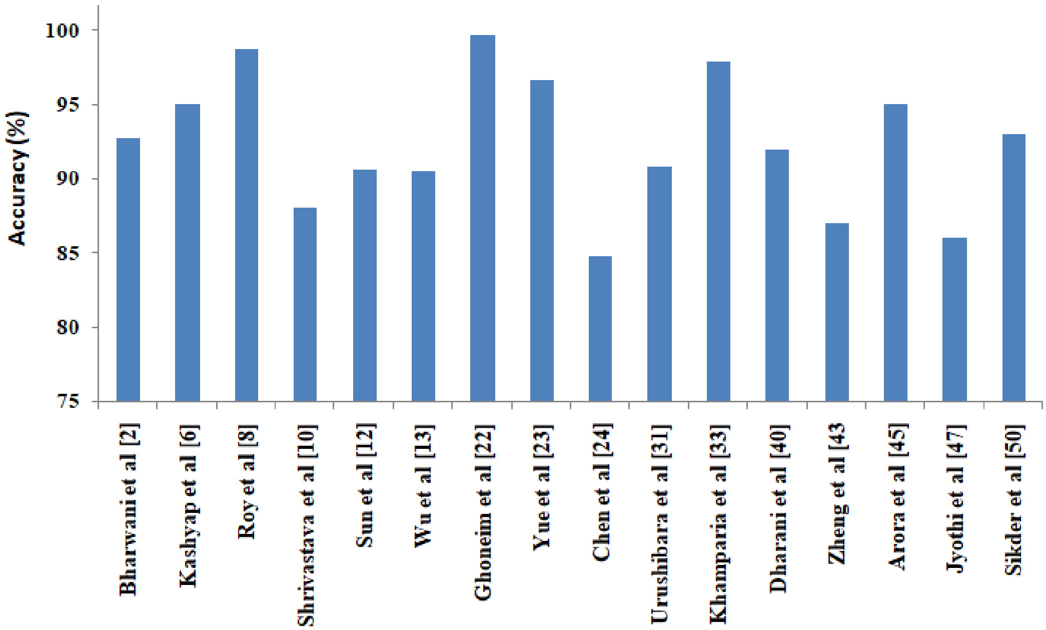


Fig.5: Performance Comparison of EC Detection Techniques in terms of Accuracy

As displayed in Fig.5 maximum accuracy of 99.7% was achieved by Ghoneim *et al* [22] and minimum accuracy of 90.48% was obtained by Chen *et al* [24]. The variation in accuracy occurs due to the variation in the dataset used for training and testing. The choice number of layers of the DNN also affects the accuracy. An analysis can also be done in terms of sensitivity and specificity which are mentioned in few of the literatures. The comparison on the basis of sensitivity is illustrated in Fig.6. The comparison on the basis of specificity is illustrated in Fig.6.

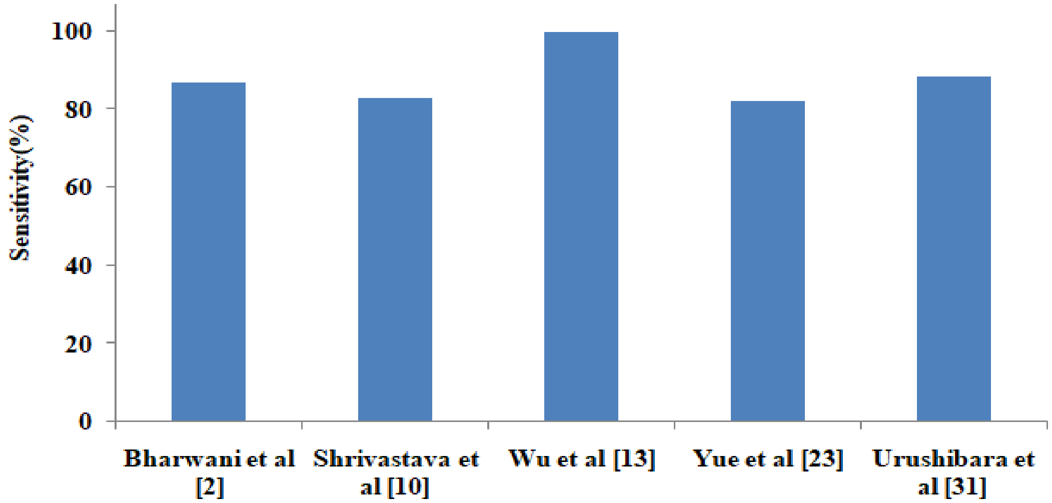


Fig.6: Performance Comparison of EC Detection Techniques in terms of Sensitivity

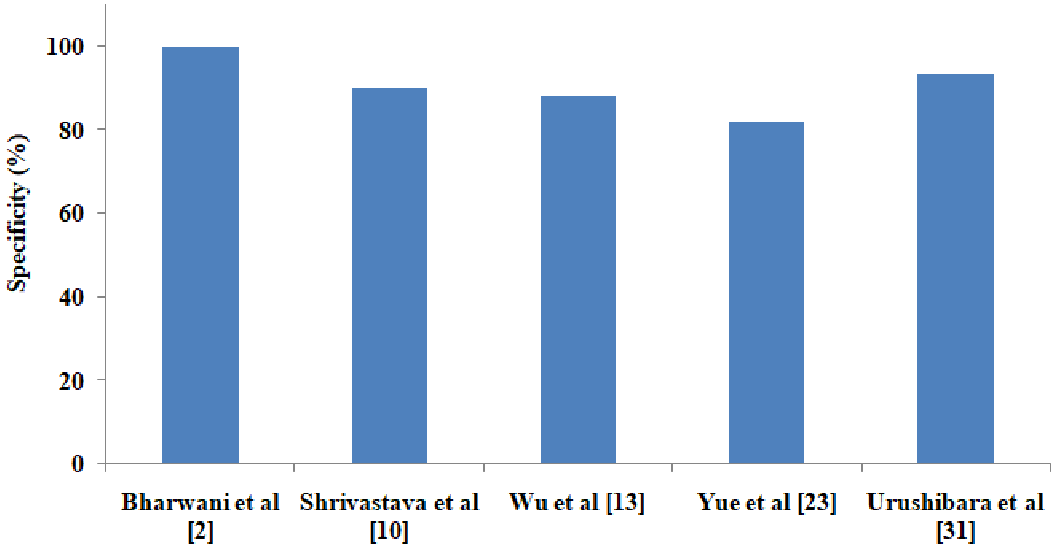


Fig.7: Performance Comparison of EC Detection Techniques in terms of Specificity

As displayed in Fig.6 maximum sensitivity of 100% was achieved by Wu *et al* [13] and minimum sensitivity of 82% was obtained by Yue *et al* [23]. As illustrated in Fig.7 maximum specificity of 100% was achieved by Bharwani *et al* [2] and minimum specificity of 82% was obtained by Yue *et al* [23]. The variation in sensitivity and specificity occurs due to the variation in the dataset used for training and testing. The choice number of layers of the DNN also affects the sensitivity and specificity. In image segmentation Dice Coefficient (DSC) is used to evaluate the performance of algorithms. Dice coefficient is a measure of similarity between the segmented output and ground truth image. The minimum value of DSC is 0 and the maximum value is 1. Dissimilar images are represented by 0 and similar images are represented by 1. The comparison of DSC is illustrated in Fig. 8.

$$DC = \frac{2TP}{2TP + FP + FN} \tag{4}$$

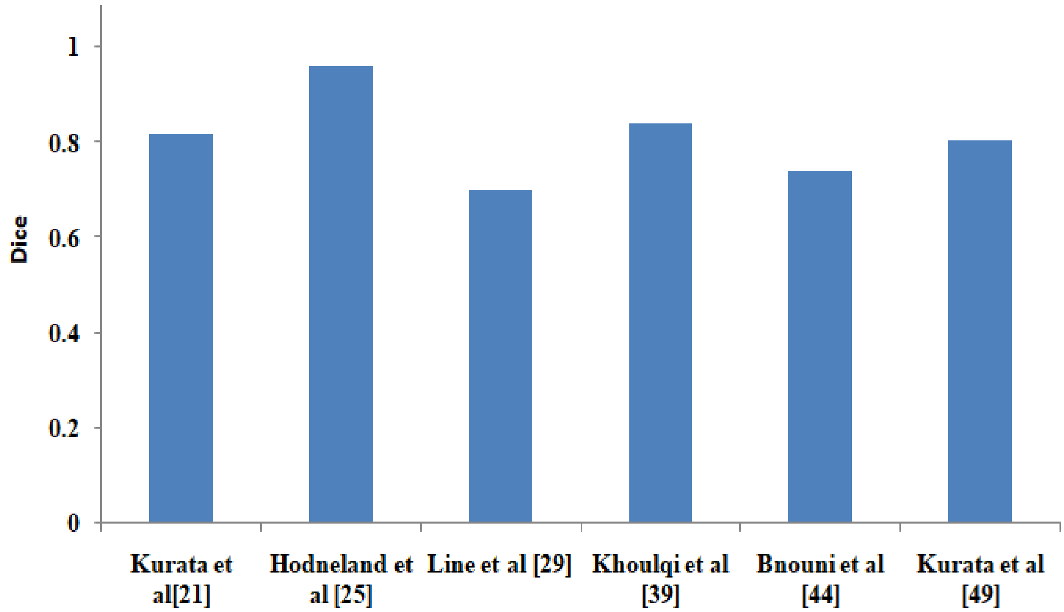


Fig.8: EC Segmentation Performance Comparison in terms of DSC

4. Conclusion

Because of the time-consuming effort required to separate endometrial cells and then identify them as healthy, anomalous, or malignant cells, detecting EC is a difficult task in medical analysis. The manual categorization of EC has a number of flaws, prompting the development of automatic or computerised classification systems. The best modality for imaging soft tissues in the endometrial region has been discovered to be MRI. The DL Neural Networks are widely employed in a variety of medical applications, and their performance results are quite accurate. The network employs a variety of designs and methodologies to identify EC at an early stage and reduce the death rate among female patients. Based on the input MRI, the CNN architecture and the factor of convolution can be either independent or dependent. Medical applications of many kinds were carried out using the CNN, which is employed for the quick and easy identification of anomalies using a variety of approaches. The network serves as a link between node structures, and the networks are evaluated using an assessment. The CNN classification algorithms give more accurate classification findings, allowing clinicians to discover EC at an earlier stage. The algorithms utilised in CNN designs can be improved further in the future for better and more promising EC detection outcomes. The capacity to transfer learning will be built in CNN in future operations, allowing it to become more efficient on a dynamic framework with excellent performance assessment.

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