Crimson Publishers
Wings to the Research

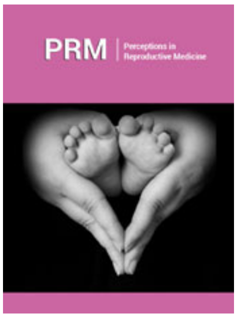
Mini Review

A Short Review for Applying Machine Learning Methods and MRI Radiomics to Endometrial Cancer Studies

Xingfeng Li*

Department of Surgery & Cancer, Imperial College, London, UK

ISSN: 2640-9666



***Corresponding author:** Xingfeng Li, Department of Surgery & Cancer, Imperial College, London, UK

Submission: April 19, 2023

Published: May 02, 2023

Volume 5 - Issue 4

How to cite this article: Xingfeng Li*. A Short Review for Applying Machine Learning Methods and MRI Radiomics to Endometrial Cancer Studies. Perceptions Reprod Med. 5(4). PRM. 000620. 2023.
DOI: 10.31031/PRM.2023.05.000620

Keywords: Endometrial cancer, Survival analysis, Radiomics, Machine learning, MRI

Mini Review

Endometrial cancer is the second most prevalent cancer among women after breast cancer with an estimated 65,950 new cases diagnosed in 2022 in the USA alone [1]. To diagnose and make a treatment plan for endometrial cancer patients, MRI scans were often employed to assess the metastasis, Depth of Myometrial Invasion (DMI), Lymph Vascular Space Invasion (LVSI), and cancer risk score with an expert. However, the accuracy of the assessment results was highly dependent on the experience and knowledge of the experts, and therefore these results were subjective. To overcome this limitation, Machine Learning (ML) methods combined with radiomics attract considerable attention for endometrial cancer studies as it is automatic and objective for the patient diagnosis. Radiomics, which is an emerging method for identifying features from medical images [2-4], have been applied for endometrial cancer classification [5,6] and survival analysis studies [7]. The current methods, results, and future directions for endometrial cancer studies using ML and MRI radiomics were presented in the following.

For endometrial cancer classification studies, DMI, LVSI, and risk score were often adopted as response variables in the ML models, while the covariates were clinical variables and/or radiomic features. Studies have shown that these response variables can be predicted with radiomic features from multisequence MRI including T1-weighted, T2-weighted, and Diffusion Weighted Imaging (DWI). Based on the radiomic features obtained from MRI, the accuracy of the endometrial cancer response variable classification accuracy is different [8]. For example, for the LVSI prediction, the Area under the Receiver Operating Characteristic curve (AUC) of 0.80 has been achieved [9]. For the DMI classification, the AUC of 0.81 was achieved using multisequence MRI [9]. However, there was smaller AUC value for the risk score stratification using radiomic features. For instance, a recent study showed that the AUC of 0.72 was obtained from the T2-weighted MRI [10] for endometrial cancer patient risk classification. For most of the studies, the risk response variable classified the patient groups into two groups only, i.e., high and low risk groups. Future studies should investigate classification methods for 4 risk groups, i.e., low, intermediate, high, and advanced endometrial cancer patient groups [6]. For the endometrial cancer histology type classification using radiomic features and clinical features, high classification results (AUC=0.90) were achieved [6].

Compared with classification studies, fewer studies focused on using survival analysis methods to investigate the survival time of the endometrial cancer patient. Survival analysis is a collection of statistical procedures for data analysis where the outcome variable of interest is the time until an event such as death or recurrence occurs [11]. For example, the 5 year overall survival rate ranges from 74% to 91% in endometrial cancer patients without metastatic disease [12], but the 5-year overall survival rate for all cancer stage IIIA patients was 55% [13]. Estimating survival time is important as it is useful for patient management and making a treatment plan. There are three methods to study survival analysis, namely, non-parametric methods such as Kaplan Meier (KM) estimate [14], semi-parametric methods such as Cox Proportional Hazard (CPH), and parametric methods. KM and CPH model methods are the most popular non-parametric and semi-parametric methods which have been carried out for endometrial survival analysis [15]. An integrated model combining clinical and radiomic features for the survival analysis has been developed [7]. In the analysis, radiomic features were incorporated into the CPH model for the survival time estimation. Although a deep learning survival analysis method has been developed [16], there is no report to use this method with radiomic features for endometrial cancer survival studies [17].

In summary, with the development of ML methods and radiomics, it is possible to classify endometrial cancer patients with a reasonable accuracy (e.g., AUC>0.8) using clinical and radiomic features. The majority of current studies adopted a handcrafted radiomics method, which requires manual segmentation of the tumour mask from medical images, while the deep learning based method is fully automatic to classify the patient into different groups for treatment [18], which is one of the future directions for endometrial cancer classification and survival analysis studies. More work needs to be done to further explore these methods and to improve the classification and survival time estimation accuracy.

References

1. Miller KD, Leticia N, Devasia T, Mariotto AB, Yabroff KR, et al. (2022) Cancer treatment and survivorship statistics, 2022. CA: A Cancer Journal for Clinicians 72(5): 409-436.
2. Mayerhoefer ME, Materka A, Langs G, Haggstrom I, Cook G, et al. (2020) Introduction to radiomics. J Nucl Med 61(4): 488-495.
3. Manganaro L, Nicolino GM, Dolciami M, Martorana F, Stathis A, et al. (2021) Radiomics in cervical and endometrial cancer. Br J Radiol 94(1125): 20201314.
4. Bibault JE, Xing L, Ayachy RE, Giraud N, Decazes P, et al. (2020) Radiomics: A primer for the radiation oncologist. Cancer/Radiothérapie 24(5): 403-410.
5. Mainenti PP, Stanzione A, Cuocolo R, Grosso RD, Danzi R, et al. (2020) MRI radiomics: A machine learning approach for the risk stratification of endometrial cancer patients. Eur J Radiol 149: 110226.
6. Li X, Dessi M, Marcus D, Russell J, Aboagye EO, et al. (2023) Prediction of deep myometrial infiltration, clinical risk category, histological type and lymph vascular space invasion in women with endometrial cancer based on clinical and T2-weighted MRI radiomic features. Cancers 15(8): 2209.
7. Li X, Marcus D, Russell J, Aboagye EO, et al. (2022) An integrated clinical-MR radiomics model to estimate survival time in patients with endometrial cancer. Journal of Magnetic Resonance Imaging.
8. Lecointre L, Dana J, Lodi M, Akladios C, Gallix B (2021) Artificial intelligence-based radiomics models in endometrial cancer: A systematic review. European Journal of Surgical Oncology 47(11): 2734-2741.
9. Lefebvre TL, Ueno Y, Dohan A, Chatterjee A, Vallieres M, et al. (2022) Development and validation of multiparametric MRI-based radiomics models for preoperative risk stratification of endometrial cancer. Radiology 305(2): 375-386.
10. Mainenti PP, Stanzione A, Cuocolo R, Grosso RD, Danzi R, et al. (2022) MRI radiomics: A machine learning approach for the risk stratification of endometrial cancer patients. European Journal of Radiology 149: 110226.
11. Clark TG, Bradburn MJ, Love SB, Altman DG (2003) Survival analysis part I: Basic concepts and first analyses. Br J Cancer 89(2): 232-238.
12. Morice P, Leary A, Creutzberg C, Rustum NA, Darai E (2016) Endometrial cancer. Lancet 387(10023): 1094-1108.
13. Lum MM, Belnap TW, Frandsen J, Brown AP, Sause WT, et al. (2015) Survival analysis of cancer patients with FIGO stage IIIA endometrial cancer. American Journal of Clinical Oncology 38(3): 283-288.
14. Kaplan EL, Meier P (1958) Nonparametric estimation from incomplete observations. Journal of the American statistical association 53(282): 457-481.
15. Fasmer KE, Hodneland E, Dybvik JA, Larsen KW, Trovik J, et al. (2021) Whole-volume tumor MRI radiomics for prognostic modeling in endometrial cancer. Journal of Magnetic Resonance Imaging 53(3): 928-937.
16. Kvamme H, Borgan, Scheel I (2019) Time-to-event prediction with neural networks and Cox regression. arXiv preprint arXiv 1907. 00825v2 20(129): 1-30.
17. Matsuo K, Purushotham S, Jiang B, Mandelbaum RS, Takiuchi T, et al. (2019) Survival outcome prediction in cervical cancer: Cox models vs deep-learning model. Am J Obstet Gynecol 220(4): 381.e1-381.e14.
18. Hosny A, Aerts HJ, Mak RH (2019) Handcrafted versus deep learning radiomics for prediction of cancer therapy response. The Lancet Digital Health 1(3): e106-e107.