Classification of Primary Fallopian Tube Carcinoma Through a Deep Convolutional Neural Network

Carson Cooper
Emily Pomerant
Madi Clark
Nicolas Gatien

Carleton University
Ottawa, Canada

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Abstract

Primary Fallopian Tube Carcinoma (PFTC) is a rare malignancy found in the female reproductive system, with a nondistinct presentation when imaged. As such, it is very difficult to diagnose preoperatively and is often misdiagnosed as Epithelial Ovarian Carcinoma (EOC), a more common malignancy, when examined on MRI scans. This high inaccuracy presents concerns due to treatment differences between the two carcinomas, resulting in a worsened patient prognosis for those who have been improperly diagnosed. Deep learning-based analysis of MRI scans has recently been shown to be effective in the diagnostic process of breast, and brain carcinomas. These AI-based analysis models have the ability to identify subtle presentation differences between carcinomas that may be missed by physicians, making it a promising method for improving diagnosis accuracy of PFTC. However, the lack of a reliable dataset of pelvic MRI scans has inhibited the production of an AI model for PFTC diagnosis. In this investigation, a dataset of retrospective MRI scans will be sourced through partnership with institutions. This dataset will be used to fine-tune ResNet-101, a Convolutional Neural Network (CNN), to differentiate MRI scans of PFTC and EOC, with an emphasis on ensuring accuracy and generalizability of the model. The goal is to produce a model that can distinguish PFTC from EOC with a higher accuracy rate than current physicians. This study has the potential to create an effective tool for physicians to accessibly, accurately, and non-invasively diagnose PFTC.

Keywords: primary fallopian tube carcinoma, PFTC, epithelial ovarian carcinoma, EOC, MRI imaging, preoperative diagnosis, convolutional neural network, AI modelling

1 Scientific Background

Primary Fallopian Tube Carcinoma (PFTC) is a rare carcinoma originating in the fallopian tubes that aggressively metastasizes across the female reproductive system. Early-stage PFTC patients only present with clinical symptoms — most of which are not pathognomonic — in approximately 15% cases.[1] The rapid metastasis and lack of unique symptoms, along with a generally non-specific tumour presentation, all lead to a common misclassification of PFTC as Epithelial Ovarian Cancer (EOC).[2] This is problematic due to distinct treatment approaches for each carcinoma. Because PFTC spreads via lymphatics, lymphadenectomy is essential for its treatment but unnecessary for EOC. Resultingly, patients with PFTC misdiagnosed as EOC often receive inadequate therapy, leading to poorer outcomes.

Current diagnostic measures for PFTC are largely insufficient. Generally, ultrasounds[2] are a first-line screening tool; though not specific for PFTC, it can confirm malignancy and prompt further testing. After ultrasound, magnetic resonance imaging (MRI) helps distinguish PFTC from EOC, but characteristic features like sausage-shaped masses and rim enhancement are not reliably identified by physicians. The large overlap in imaging criteria for PFTC and EOC means imaging methods are effective in PFTC diagnosis for less than 5% of cases.[3] As such, diagnosis of PFTC often resorts to operative diagnosis, which, while effective in 30-50% of cases, is a very invasive process.[4] No standard non-invasive method reliably distinguishes PFTC from EOC.

Existing literature demonstrates the effectiveness of deep convolutional neural networks (DCNN) such as ResNet-101 for accurate classification and identification of carcinoma types within a single organ based on MRI scans alone.[5–7] While these neural networks have been proven effective in diagnosis of other cancer types, no dataset of sufficient size for accurate model building (>600 patients)[5] has been assembled for the female reproductive tract, halting model creation for PFTC and EOC. The non-invasive nature of neural networks make them an enticing option for the reliable differentiation of PFTC from EOC.

2 Research Hypothesis

This investigation will evaluate the accuracy of a fine-tuned DCNNs on pelvic MRI slices in differentiating PFTC from EOC. Pelvic MRI scans will be uploaded to ResNet-101, a DCNN often used for image classification, which will be trained to identify morphological differences between PFTC and EOC. The network will then generate a probability score that identifies new images as one of the two carcinomas. Using this model, we predict that the proportion of correctly classified PFTC cases can be increased compared to current physician identification methods.

3 Rationale

By introducing advanced deep learning architecture like ResNet-101 to pelvic MRI scans, this study aims to deliver a transformative, non-invasive solution. DCNNs excel at analyzing large, complex medical images and can capture subtle spatial and textural distinctions that may elude even experienced radiologists. ResNet-101 has already demonstrated high performance across diverse imaging modalities in oncology. It can learn highly discriminative representations from MRI scans, highlighting nuanced differences in lesion morphology, margins, and tissue enhancement that distinguishes PFTC and EOC. The expected outcomes of this investigation are twofold: first, more reliable and earlier differentiation of PFTC and EOC, improving the allocation of surgical and post-operative interventions; second, reduced reliance on invasive diagnostics, minimizing patient risk. Integrating this refined AI-based model into clinical practice can significantly enhance decision-making and survival outcomes for women facing these rare carcinomas.

4 Methodology

This investigation will consist of acquiring retrospective data on pelvic MRI scans, which will be used to process and train a DCNN. Additional data will be used to assess the accuracy of the developed model.

4.1 Data Collection

There exists no publicly accessible large-scale dataset of pelvic MRI images for PFTC and EOC. As such, the assembly of our own dataset is necessary. Through partnership with institutions we can ethically collect retrospective data. Assembling a cross-institutional dataset presents challenges such as storing the data and working with the unique standards of each institution.[8]

4.2 Data Processing

For each patient only the MRI slice where the tumour has the greatest surface area will be added to the dataset. The slice will be scaled down to 256x256 pixels, and labeled with its corresponding carcinoma. Our dataset will have two categories of carcinomas: "PFTC" and "EOC".

After preprocessing, we will follow the same data augmentation steps demonstrated for the classification of brain tumours: random vertical and horizontal mirroring, and adding a layer of gaussian noise on 10% of the samples. Augmenting the data will minimize the risk of overfitting on data from any given institution (which may have its own pattern of noise).[9]

4.3 Fine-Tuning

We will use ResNet-101[10] pretrained on ImageNet as a base model. Fine-tuned ResNet-101 models have been used in the classification of tumours.[5] ImageNet is a large-scale dataset of real-world images used to train image classification models. A pretrained version of ResNet-101 can be implemented using Pytorch, and fine-tuned based on a given dataset. Our dataset will be split into training and hold-out subsets following a 70/30 ratio. During fine-tuning, the model will only be exposed to the training set, allowing us to test how well the model generalizes to new examples (hold-out set).

4.4 Accuracy Evaluation

As outputs, the fine-tuned ResNet-101 model will be constrained to the options of the dataset (PFTC & EOC). After scanning an MRI slice, the model will output confidence scores for each type of carcinoma. The accuracy of these scores can then be evaluated and compared to traditional physician diagnosis accuracy.

5 Conclusion

PFTC is often misclassified as EOC due to overlapping clinical and imaging features, resulting in suboptimal treatment and negative outcomes for affected patients. This research proposal highlights the critical need for improved, non-invasive diagnostic tools that can accurately distinguish PFTC from EOC. Leveraging recent advancements in deep learning, a ResNet-101 DCNN that is pretrained on a large-scale image dataset and fine-tuned on pelvic MRI scans could offer a highly robust solution for this challenging health issue. This model could improve diagnostic accuracy, reduce invasive procedures, and support timely treatment decisions and implementations. Investment in comprehensive datasets and rigorous validation will be essential to realizing this approach. AI-driven diagnostics could greatly improve outcomes and quality of life for women with rare gynecologic carcinomas.

Definition Sheet

Primary Fallopian Tube Carcinoma (PFTC): Rare malignant carcinoma with a vague presentation, similar to that of EOC, that originates in the fallopian tubes and rapidly spreads throughout the entire female reproductive system

Pathognomonic: Symptom that is unique to a specific condition

Metastasis: Spread of cancerous cells away from the tumour's point of origin

Epithelial Ovarian Carcinoma (EOC): Common form of ovarian cancer originating on the epithelial cells of the ovaries

Lymphadenectomy: Surgical removal of one or more groups of lymph nodes, commonly practiced in the surgical treatment of tumours

Ultrasound: Non-invasive imaging technique that uses high-frequency sound waves to produce real-time pictures and videos of organs and soft tissues. Often used as a primary imaging modality in PFTC screening

Magnetic Resonance Imaging (MRI): Non-invasive imaging technique that uses excitation of a rotational axis of protons to produce high contrasts, three-dimensional anatomical images of soft tissues. Often used to differentiate PFTC from EOC, with minimal success rates

Rim Enhancement: Pronounced annular enhancement belt surrounding lesions visible on MRI scans, that is often highly visible in PFTC

Convolutional Neural Network: Type of neural network which makes use of convolutional layers to downsample input data. The downsampling is a process of applying filters (typically to images) to extract features of the image instead of raw pixel data

Retrospective data: Existing data that has been previously collected for separate purposes, being reused to examine new patterns. Many forms of medical records, including accurately identified MRI scans of patients with PFTC or EOC, are forms of retrospective data

Gaussian noise: Layer of random distortions which follow a Gaussian distribution applied to an image

PyTorch: Python library used for AI development

Citations

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