Deep learning approaches for handling longitudinal image data: Enhancing breast cancer prediction

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Résumé

Breast cancer remains a predominant cause of global cancer-related death in women. Despite the widespread implementation of mammography-based screening programs, irregular visit frequencies and intervals between screenings pose a substantial challenge to current deep-learning methods. Initially designed for static datasets, these methods lack the adaptability required for the dynamic nature of longitudinal image data. This study aims to address this gap by developing and comparing deep-learning methods tailored to handle longitudinal mammograms obtained during breast cancer screening while accounting for irregular visits and irregular time intervals.

Using sequential mammography exams of 77,298 women involved in breast cancer screening in the US, we predict breast cancer risk through the implementation of the following methods. First, focusing on women with exactly four visits, we use a combined CNN-RNN model where the architecture mirrors the LRP-NET model(1), with the VGG16 replaced by a pre-trained mammogram model for swift training. Second, to incorporate variable visit sequences, we extend our approach by introducing padding masks within the RNN block to account for gaps in the sequence. We include an embedding to specify the precise location of the padding mask within the sequence, ensuring that the model recognizes these placeholders and does not update the weights based on the padding values. On the other hand, a generative time-to-event model(2), integrating an Ordinary Differential Equation-based RNN as an encoder, is adjusted to image data addressing irregular visits and spacing across women, providing an evaluation of the temporal evolution in image features and their impact on risk prediction. Performance is assessed through a woman-wise 5-fold cross-validation process, and all the methods are compared using the ROC AUC.

This study introduces and compares multiple deep-learning methods tailored for longitudinal image data with application to breast cancer screening, adeptly handling irregular visit frequencies and intervals. Through comprehensive evaluations, we assess the predictive performance of these methods, providing insights into optimizing breast cancer risk assessment in the context of accumulated imaging information.

References

(1) Dadsetan et al., Pattern Recognition, 2022

(2) Moon et al., PMLR, 2022

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