Assessing Risk of Prostate Cancer Metastasis by Deep Learning in Surgically-Treated Patients

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Overview

- Prostate cancer is among the most prevalent types of cancer in males. More than 90 percent of patients without metastasis are expected to live at least five years, whereas patients with metastatic prostate cancer have a much poorer prognosis.
- Localized prostate cancer is commonly treated by radical prostatectomy (RP). Within 10 years, up to one-third of men who have undergone RP for clinically organ-confined prostate cancer develop a biochemical recurrence (BCR) and can ultimately develop metastases associated with a high mortality rate.
- Determining the risk of metastasis in prostate cancer patients after radical prostatectomy is challenging, and there are no effective risk prediction techniques. Current techniques largely rely on pathology data, such as primary and secondary Gleason scores, reporting of which is highly subjective and subject to inter- and intra-observer variation.
- Currently, there are no effective AI-based techniques for predicting the likelihood of metastasis in patients following radical prostatectomy.

Methodology – Concatenated Feature Based Classification (CFBC)

- **Tumor Identification**: A SegFormer [1] model was trained on WSI patches of Radical Prostatectomy for tumor segmentation.
- **Clinical Feature Module**: A Self-Supervised Learning model was trained using DINO methodology and a large quantity of existing prostate data (more than 10000 WSIs). The features generated by this module served as baseline morphological biomarkers for outcome prediction tasks in subsequent modules.
- **Feature Extraction**: ResNeXt50's SSL weights were used for patch-level feature extraction. This network was used to convert all 256x256x3 patches into 8x8x2048 representations. The characteristics of NxN regions are concatenated to create an 8Nx8Nx2048 tensor.
- **Classification**: As a classification network, ResNet18 was utilized. In addition to the 8Nx8Nx2048 tensor, the network was modified to include clinical parameters as input. As a branch that receives clinical data and outputs a 256-dimensional vector, a two-layer, fully connected network was created. The output of ResNet18's penultimate layer was concatenated with this vector. Finally, the concatenated vector was passed through a fully connected layer that generated the logits for metastasis classification.

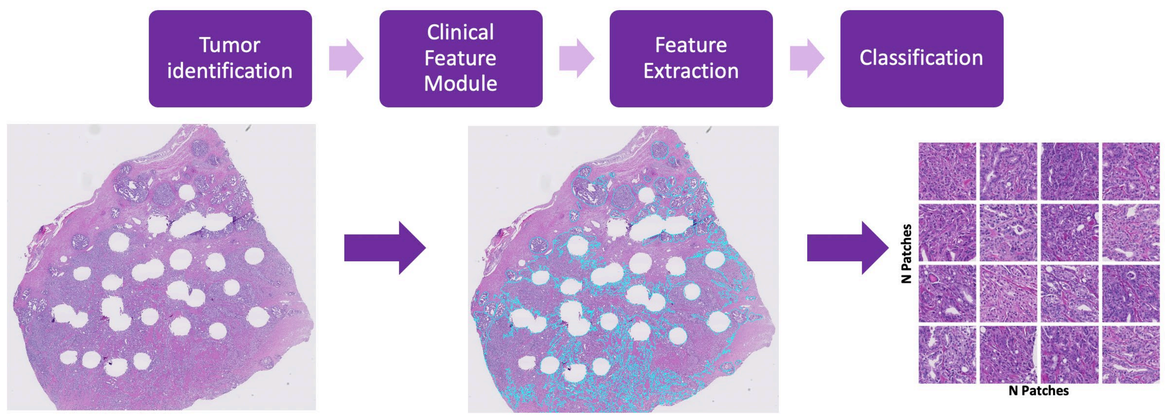

Figure 1. Concatenated Feature Based Classification (CFBC)

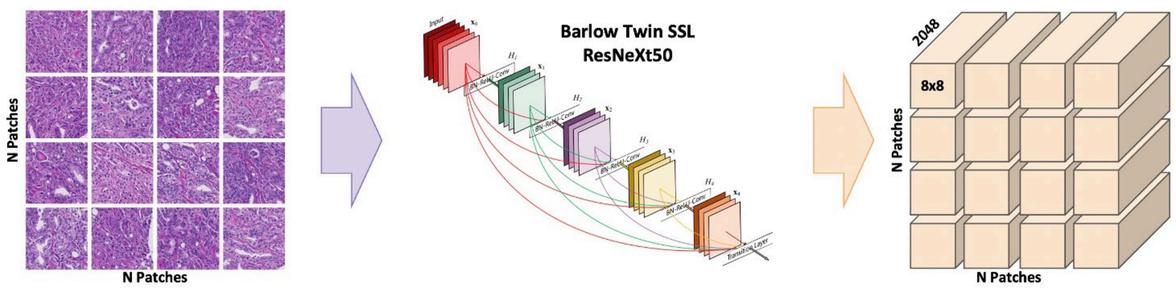

Figure 2. Feature Extraction. 8x8 feature space for each patch with 2048 channels

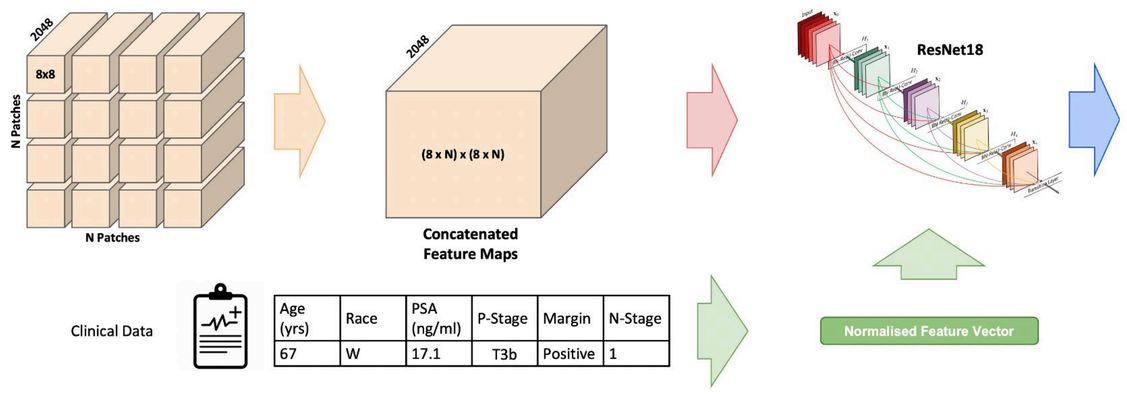

Figure 3. Classification Module.

Explainability

- The final stage involved the generation of a visual heatmap that highlighted the image region that corresponds to the predicted outcome.
- 1024 x 1024 overlapping regions were isolated from the tumour region at 20x magnification using a sliding window technique with 128 x 128-pixel step size.
- Using the inference of the classification model, an AI score is estimated for each patch.

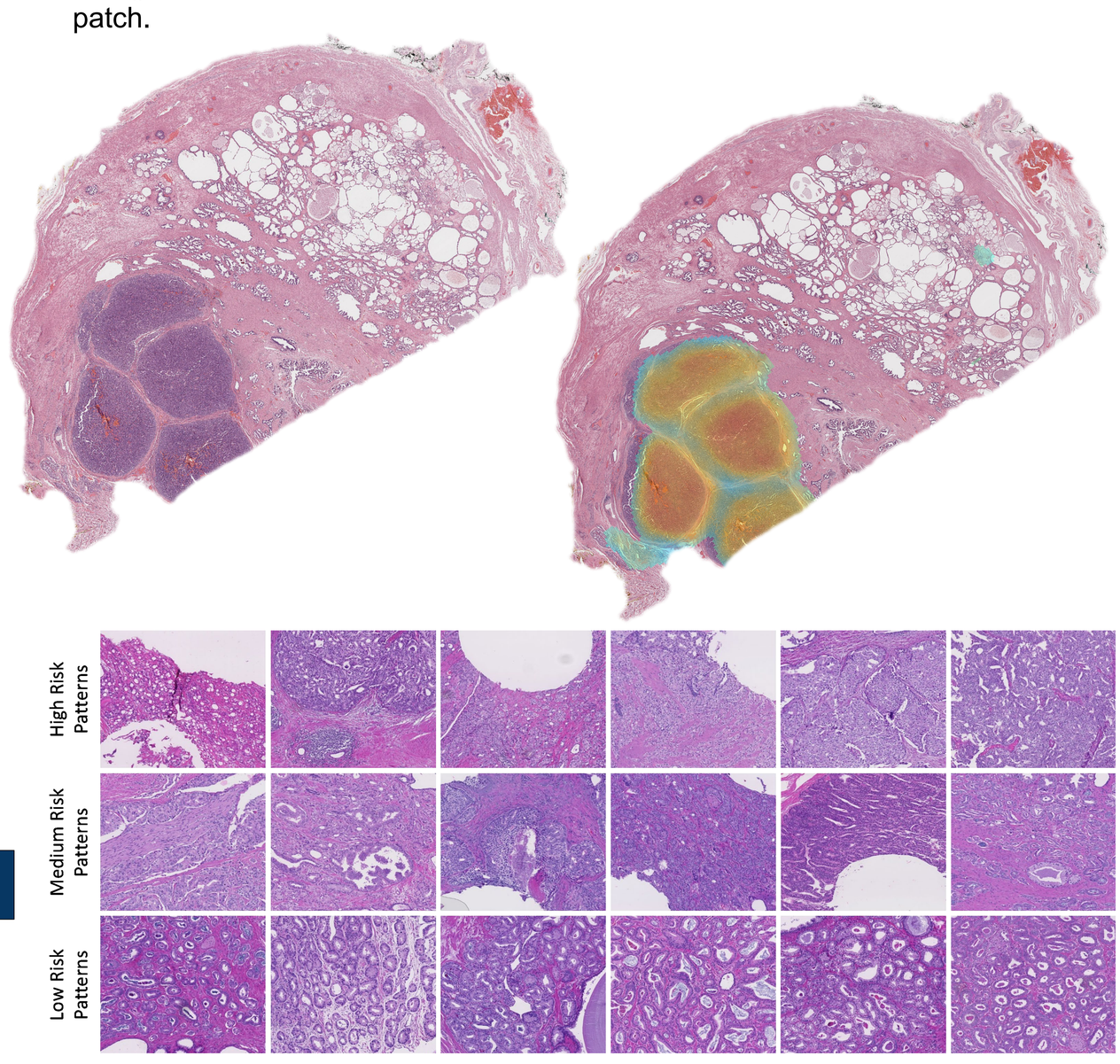

Figure 4. The interpretation of AI risk scores in relation to individual patterns. Gleason patterns 4 and 5 are predominant among lesions with a high risk of metastasis. Patterns consisting primarily of stroma and a lower Gleason grade (Gleason pattern 3 and well-formed glands) indicated lower risk scores.

Results

	Training	Testing
# Patients	724	181
# Patients with Metastasis	158	40

Table 1. Training and Testing data. Scanner – Hamamatsu Nanozoomer XR. Retrospective case-cohorts from Johns Hopkins
[1] Ross, Eur Urol, 2016; [2] Trock, J Urol, 2022; [3] Weiner, Nat Commun, 2021

Variable Group	Clinical Parameters	Clinical Parameters + Pathologist Gleason Grading	CAPRA-S	WSI Images	WSI Images + Clinical Parameters	WSI Images + Clinical Parameters + Pathologist Gleason Grading	TMA Images	TMA Images + Clinical Parameters
Logistic regression	**0.819** ± 0.019	**0.859** ± 0.019	**0.851** ± 0.026	-	-	-	-	-
Deep Learning Model	-	-	-	**0.871** ± 0.017	**0.899** ± 0.009	**0.904** ± 0.011	**0.877** ± 0.011	**0.896** ± 0.007

Table 2. AUC performance

Conclusion

- We present a multi-modality deep learning system to predict the likelihood of metastases in patients post radical prostatectomy.
- We train and evaluate the system using multi-modality data such as histopathology images and clinical data from a cohort of patients with long-term follow-up.
- Initial studies provide proof-of-principle for deep learning algorithms to predict metastatic outcomes.
- Larger, multi-institutional cohorts are required for further validation.

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