



Introduction

Hepatocellular carcinoma (HCC) ranks among the leading causes of cancer-related mortality, with post-transplant recurrence exceeding 20%. Traditional tools like the Milan Criteria focus on tumor size and number but fail to account for biological heterogeneity, limiting their predictive accuracy. Moreover, key histological markers, such as microvascular invasion, are assessable only post-surgery.

To address these gaps, we propose a novel framework combining DINOv2-based self-supervised learning (SSL) for feature extraction with survival analysis for time-dependent risk prediction. Using data from 127 HCC patients, including 19 recurrence cases, the model aims to provide a reliable, non-invasive tool for preoperative risk stratification, advancing personalized HCC management.

Experiment Setup

1. External Datasets for Pre-training: Pre-training utilized four publicly available datasets, comprising over 330,000 MRI images, to establish robust feature representations for liver pathologies and multi-organ segmentation tasks:

- LLD-MMRI: Liver lesion detection and segmentation.
- CHAOS: Multi-modal imaging with liver segmentation.
- LiverHCCSeg: HCC-specific tumor localization and segmentation.
- AMOS: Diverse imaging for robust liver segmentation features.

2. Benchmarking Dataset: The Duke Liver Dataset was used for benchmarking, with annotated MRI images and clinical data for HCC cases:

- Series Classification:** MRI sequence categorization to optimize sequence-specific features.
- Liver Segmentation:** High-quality masks for accurate liver localization and segmentation evaluation.

3. Internal Dataset (NYU Langone Health) For Fine-Tuning: including clinical data, tumor characteristics and subgroup analyses. IRB challenges delayed access during the project, but future work will incorporate this dataset.

- 127 liver transplant patients.
- 19 recurrence cases.
- IRB-approved (s24-01191).

Method

We propose a novel framework that integrates self-supervised learning with survival analysis to predict early HCC recurrence. Our approach combines advanced imaging analytics with time-dependent risk modeling to provide comprehensive recurrence prediction.

Framework Components:

- DINOv2-based feature extraction from MRI scans
- Time-to-event survival analysis modeling
- Integration of high-dimensional imaging features

Result

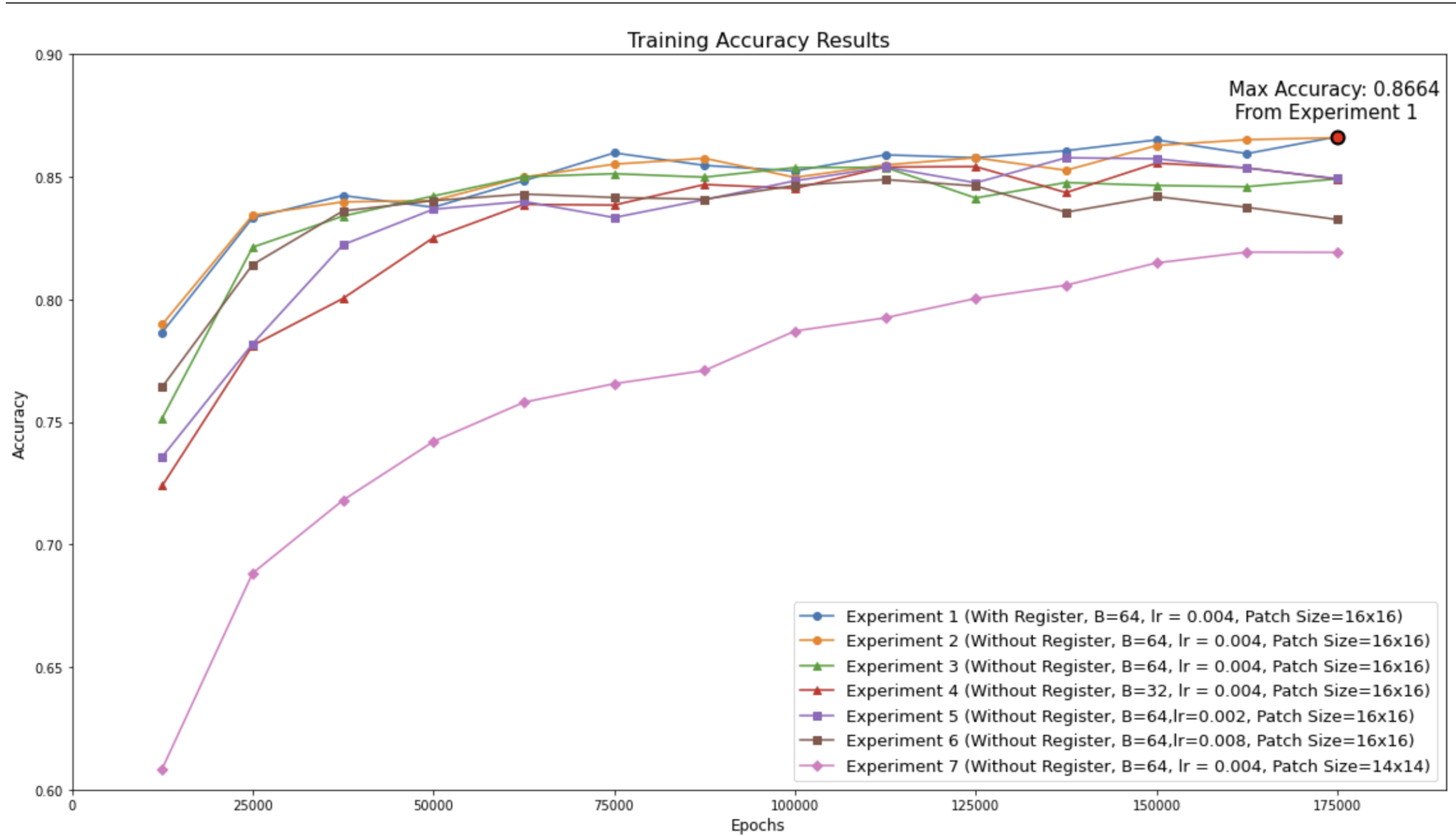


Figure 1. Training accuracy trends across different model configurations.

Figure 1 illustrates the accuracy trends across training epochs for all experiments, highlighting the impact of different configurations such as register usage, batch size, learning rate, and patch size on model performance. Among these, Experiment 1, which employed register tokens, a batch size of 64, a learning rate of 0.004, and a patch size of 16×16, achieved the highest accuracy of 0.8664. Experiment 2, which excluded register tokens, performed comparably with an accuracy of 0.8660. Models with smaller patch sizes, such as Experiment 7 (14×14), demonstrated lower accuracy, emphasizing the importance of patch size in feature extraction.

Model	With Register	Batch Size	Learning Rate	Patch Size	Accuracy
Random Baseline	-	-	-	-	0.82
Pretrained Model	-	-	-	-	0.85
Experiment 1	Yes	64	0.004	16×16	0.8664
Experiment 2	No	64	0.004	16×16	0.8660
Experiment 3	No	64	0.004	16×16	0.8539
Experiment 4	No	32	0.004	16×16	0.8556
Experiment 5	No	64	0.002	16×16	0.8578
Experiment 6	No	64	0.008	16×16	0.8489
Experiment 7	No	64	0.004	14×14	0.8193

Table 1. Accuracies Across Models with Varying Hyper-parameters.

Table 1 summarizes the final accuracy values for all experiments, including comparisons with the random baseline and pretrained models. The random model, initialized with random weights, achieved an accuracy of 0.82, while the pretrained model using the DINOv2 self-supervised learning (SSL) framework on external MRI datasets achieved a higher accuracy of 0.85. Experiments 1–7 showcase the importance of hyperparameter optimization, with Experiment 1 outperforming both baselines. These findings underscore the significance of register tokens and carefully tuned hyperparameters in improving model performance.

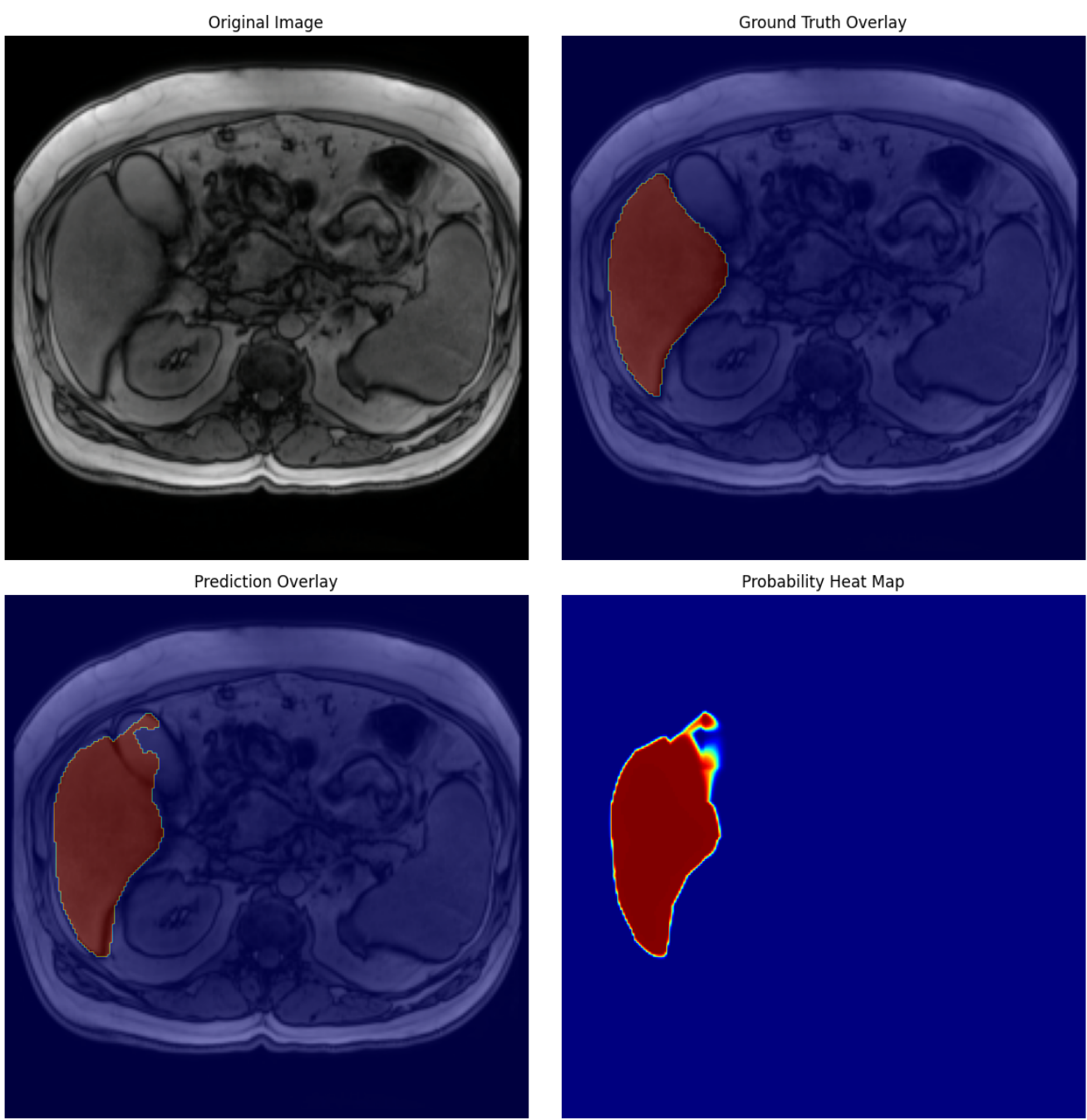


Figure 2. Segmentation Prediction

As another benchmark for our DINOv2 output, we utilize the patch tokens of DINOv2 to perform a segmentation task on the Duke Liver Dataset. Specifically, we train a segmentation head using these patch tokens, which achieves a Dice score of 0.92, outperforming the pretrained weights, which yielded a Dice score of 0.90. This improvement underscores the capability of the optimized patch tokens to enhance downstream segmentation tasks, further validating the effectiveness of our experimental configurations in leveraging DINOv2 for medical imaging applications.

Discussion

Our pretraining experiments with DINOv2 demonstrated the potential of self-supervised learning for medical imaging tasks, particularly in HCC recurrence prediction. While results are promising, several important considerations emerged.

- Strengths:**
 - Strong performance in classification and segmentation
 - Successful feature extraction from heterogeneous data
 - Robust framework for medical imaging analysis
- Current Limitations:**
 - Pending fine-tuning on NYU internal dataset
 - Potential biases in external pretraining datasets
 - Incomplete time-to-event prediction validation
- Impact Assessment:**
 - Demonstrated viability of SSL for medical imaging
 - Established foundation for clinical implementation
 - Identified key areas for enhancement

Conclusion

We developed a framework integrating self-supervised learning (SSL) with DINOv2 and survival analysis, achieving 0.8664 accuracy on the Duke Liver Dataset for HCC recurrence prediction. Limited by the lack of fine-tuning on internal data, future work will focus on multi-center validation and clinical data integration to enhance performance. This study highlights SSL's potential in personalized HCC management.