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A. Data Preprocessing

A.1. HCC-TACE-Seg dataset preprocessing

The HCC-TACE-Seg dataset [55] refers to a single-institution collection of patients with confirmed hepatocellular carcinoma (HCC) who were treated at The University of Texas MD Anderson Cancer Center. Data preprocessing for HCC-TACE-Seg involves resampling the provided CT images to a standardized spatial resolution while preserving the integrity of the original data structure. Specifically, images and masks are resampled to a target spacing of 0.8mm × 0.8mm × 3.0mm to standardize voxel dimensions across different cases.

Longitudinal Registration: Accurate image registration is essential to ensure that tumor boundaries are clearly defined across both the liver and HCC regions in different imaging modalities, such as arterial phase (AP) and portal venous phase (PVP) scans. The longitudinal registration process involves aligning the post-AP image to the pre-AP image, and the post-PVP to the pre-PVP image, addressing any misalignments between scans. Both linear and non-linear registration methods are employed through the open-sourced registration framework deedsBCV [1] for optimal alignment.

Liver and HCC Cancer Segmentation: We utilize a nnUNet-based [38] mode trained on the public LiTS dataset [5] for liver and HCC cancer segmentation. For postprocessing, we adopt connected component analysis to extract the liver and HCC regions precisely. This approach ensures that the tumor and liver boundaries are defined clearly, which is crucial for downstream analysis. An example of pre- and post-treatment CT images, along with liver and tumor segmentation generated from the HCC-TACE-Seg dataset, is shown in Figure 8.

We also conduct a Component Size Filtering strategy. A component size filtering step is applied, with a minimum threshold of 300 voxels, ensuring the accurate identification of tumor and liver regions. This step helps to remove noise or irrelevant small regions, improving the precision of segmentation results. Only the image data paired with the following meta-information are selected for further analysis:

- Chemotherapy: Information about whether the patient underwent chemotherapy treatment, including details about the type of chemotherapy regimen.
- Overall survival: Overall survival time in months.
- Survival status: 0 indicates that the patient is alive or lost to follow-up, while 1 indicates death. Details are in Table 4.

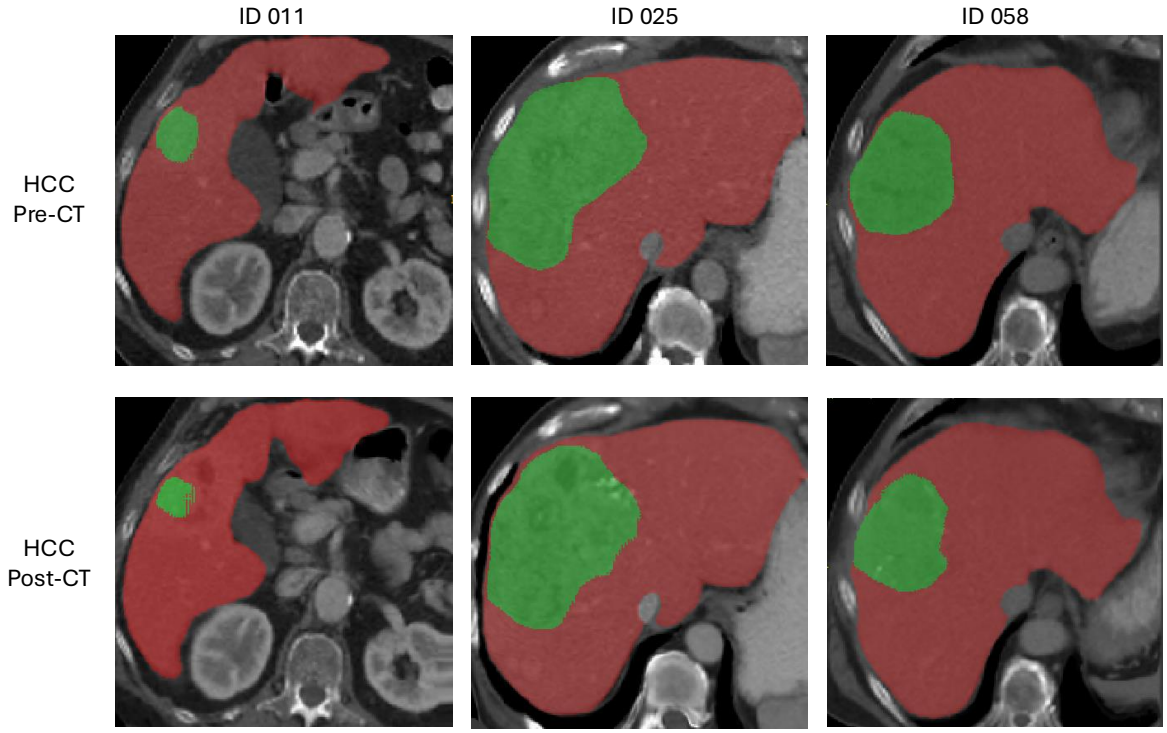

Figure 8. Example of HCC-TACE-Seg dataset. The first row shows HCC Pre-CT images, and the second row shows HCC Post-CT images. The red mask represents the liver, while the green mask represents the HCC tumor.

Patient ID	Chemotherapy	Overall Survival (months)	Survival Status
HCC_009	Cisplatin; Doxorubicin; Mitomycin; Lipiodol	4.7	1.0
HCC_011	Cisplatin; Doxorubicin; Mitomycin; Lipiodol	19.3	1.0
HCC_025	Cisplatin; Doxorubicin; Mitomycin; Lipiodol	30.0	1.0
HCC_034	Doxorubicin; Lipiodol; LC beads	18.9	1.0
HCC_042	Cisplatin; Mitomycin; Lipiodol	34.1	1.0
HCC_051	Cisplatin; Mitomycin; Lipiodol	12.9	1.0
HCC_058	Cisplatin; Mitomycin; Lipiodol	87.0	0.0
HCC_067	Cisplatin; Doxorubicin; Mitomycin; Lipiodol	90.9	0.0
HCC_079	Doxorubicin; LC beads; Lipiodol	42.5	1.0
HCC_091	Doxorubicin; LC beads; Lipiodol	25.3	0.0

Table 4. An example of HCC-TACE-Seg dataset metadata, including chemotherapy, overall survival, and survival status. For survival status, a value of 0 indicates that the patient is alive or lost to follow-up, while a value of 1 indicates death.

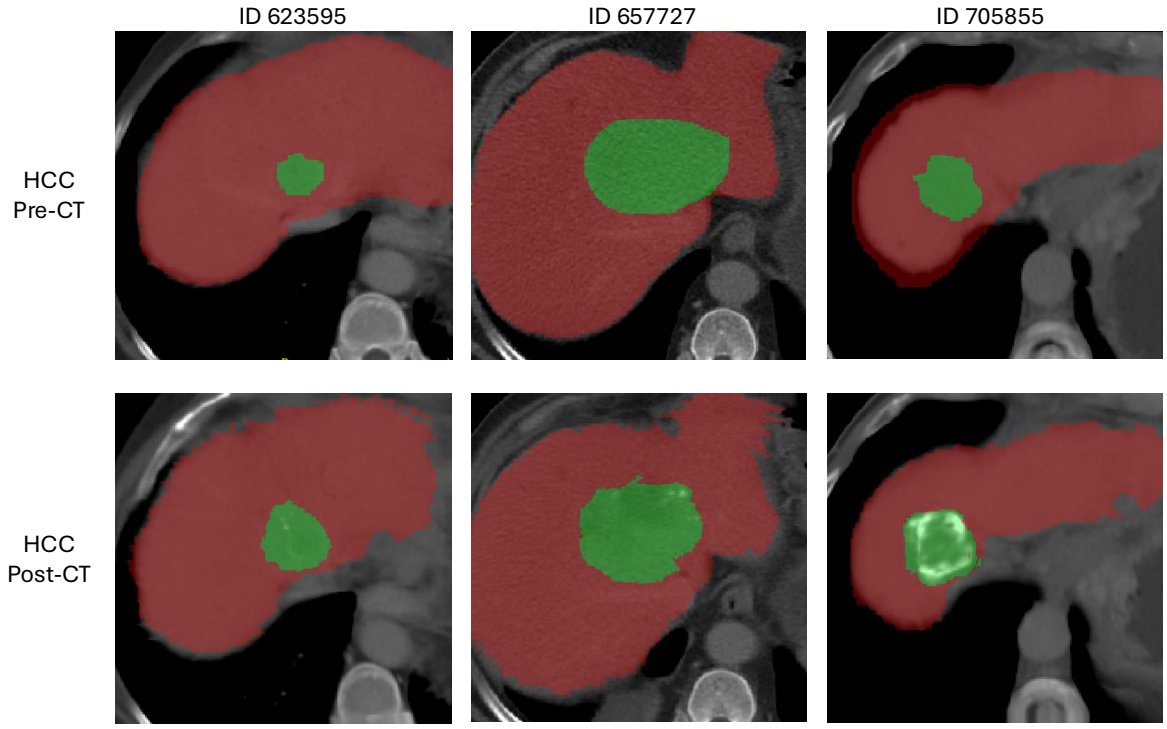

Figure 9. Example of HCC-TACE dataset. The first row shows HCC Pre-CT images, and the second row shows HCC Post-CT images. The red mask represents the liver, while the green mask represents the HCC tumor. In post-treatment CT imaging of HCC, particularly after Transarterial Chemoembolization (TACE), the viable tumor region and its enhancement intensity decrease due to Lipiodol accumulation and treatment-induced necrosis. Lipiodol appears hyperdense (bright) on post-treatment CT, indicating areas that have been successfully embolized.

Patient ID	Processed Chemotherapy	OS (months)	Survival Status
HCC_08116730	Raltitrexed 4 mg was infused through the catheter; 5 ml ultra-liquid Lipiodol and 5 mg Epirubicin were mixed to create an emulsion for embolization; the emulsion was slowly injected under fluoroscopic guidance; an appropriate amount of Gelatin Sponge particles was used to embolize the tumor-feeding branches of the S8 segment of the right hepatic artery; Lipiodol deposition in the tumor was satisfactory; tumor-feeding arteries were occluded on the final angiography.	1.4	0.0
HCC_01061677	THP 10 mg was infused through the catheter; 10 mg THP and 10 ml ultra-liquid Lipiodol were mixed to create an emulsion for embolization; 12 ml of the emulsion was slowly injected under fluoroscopic guidance; Lipiodol deposition in the tumor and satellite lesions was satisfactory; tumor-feeding arteries were occluded on the final angiography.	75.7	1.0
HCC_01192613	THP 40 mg and 30 ml ultra-liquid Lipiodol, along with a small amount of contrast agent, were mixed to create an emulsion for embolization; 30 ml of the emulsion was slowly injected under fluoroscopic guidance; a small amount of Gelatin Sponge particles was used for embolization; Lipiodol deposition in the tumor was satisfactory; no tumor staining was observed on the final angiography.	84.6	1.0
HCC_01204059	Cisplatin 40 mg was infused through the catheter; 10 ml ultra-liquid Lipiodol was slowly injected under fluoroscopic guidance for embolization of the right hepatic artery tumor-feeding branches; 3 ml ultra-liquid Lipiodol was injected for protective embolization of the segment II branch of the left hepatic artery; Lipiodol deposition in the tumor was acceptable; tumor staining mostly disappeared on the final angiography.	17.1	0.0
HCC_01532843	Oxaliplatin 100 mg and Epirubicin 30 mg were infused through the catheter; 10 mg Epirubicin and 10 ml ultra-liquid Lipiodol were mixed to create an emulsion for embolization; 10 ml of the emulsion was slowly injected under fluoroscopic guidance; an appropriate amount of Gelatin Sponge particles was used to embolize the tumor-feeding branches of the right hepatic artery; Lipiodol deposition in the tumor was satisfactory; tumor staining disappeared on the final angiography.	29.3	1.0
HCC_01532843	Epirubicin 40 mg and Oxaliplatin 100 mg were infused through the catheter; 10 ml ultra-liquid Lipiodol was slowly injected under fluoroscopic guidance for embolization; Lipiodol deposition in the tumor was satisfactory; tumor-feeding arteries were mostly occluded on the final angiography.	21.6	1.0

Table 5. An example of HCC-TACE dataset metadata, including chemotherapy, overall survival, and survival status. For survival status, a value of 0 indicates that the patient is alive or lost to follow-up, while a value of 1 indicates death.

A.2. HCC-TACE dataset preprocessing

The HCC-TACE dataset is a large-scale, self-collected repository containing 338 longitudinal pairs of pre- and post-treatment CT scans, along with well-annotated liver and tumor masks, as well as clinical records. These records include TACE radiotherapy reports (considered the gold action) and Overall Survival (OS) time. Details are presented in Table 5. The dataset is split into training (including validation) and testing sets in a 9:1 ratio. All images and masks are resampled to a target spacing of 0.8mm × 0.8mm × 3.0mm to standardize voxel dimensions across different cases.

Longitudinal Registration: We also employ deedsBCV [1] to align the post-AP image with the pre-AP image, and the post-PVP image with the pre-PVP image, addressing any misalignments between the scans.

Liver and HCC Cancer Annotation: In this dataset, all liver and tumor masks for each CT scan are carefully annotated by radiologists. For postprocessing, we also apply connected component analysis to accurately extract the liver and HCC regions. An example of pre- and post-treatment CT images, along with liver and tumor segmentation generated from the HCC-TACE dataset, is shown in Figure 9.

B. Implementation Details

B.1. Policy Model

We adopt GPT-4o to obtain the initial observation from the given pre-treatment CT scans and collect the individualized potential drugs and embolism during TACE treatment. An example is presented in Figure 10. Then, we refine the action set using DeepSeek-R1 [25], which reasons the clinical conflicts in the current action set and summarizes a better action set using clinical guidelines for individuals (*e.g.*, Multiple platinum-based drugs cannot be used simultaneously).

B.2. Dynamics Model

In this study, we implement Dynamics Model by training the corresponding Diffusion Model [47] specifically from pre-treatment liver tumors to post-treatment liver tumors. The CT scans are oriented according to specific axcodes and resampled to achieve isotropic spacing of $1.0 \times 1.0 \times 1.0$ mm^3. $96 \times 96 \times 96$ patches are randomly cropped around either foreground voxels based on a set ratio. Their intensities are truncated to the range $[-175, 600]$ to maintain the discrimination of lipiodol/necrosis/viable areas [31], then linearly normalized to [-1, 1]. We utilize the Adam optimizer with hyperparameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$, a learning rate of 0.0001, and a batch size of 10 per GPU. The training is conducted on A6000 GPUs for 2 days, over a total of 2,000 iterations.

B.3. Assistant Model

We employ a nnUNet-based [38] segmentation model for the segmentation of liver and tumor in post-treatment CT. As suggested by Chen *et al.* [14], we generate realistic tumor-like shapes using ellipsoids, and combine these generated tumor masks with the healthy CT volumes to create a range of realistic liver tumors. We pre-train the model on the generated and real tumors for robust generalization. Then, we finetune it on post-treatment CT scans as well as liver and tumor masks. The implementation is in Python, leveraging MONAI*. The CT scans are oriented according to specific axcodes and resampled to achieve isotropic spacing of $1.0 \times 1.0 \times 1.0$ mm^3. Their intensities are truncated to the range $[-175, 600]$ to maintain the discrimination of lipiodol/necrosis/viable areas, then linearly normalized to [-1, 1]. During training, $96 \times 96 \times 96$ patches are randomly cropped around either foreground or background voxels based on a set ratio. Each patch is subjected to a 90° rotation with probability 0.1 and an intensity shift of 0.1 with probability 0.2. To avoid confusing the left and right organs, mirroring augmentation is not used.

The model is initialized with pre-trained liver tumor weights from DiffTumor [14], then fine-tuned on our dataset for 2,000 epochs. We set the base learning rate to 0.0002 and use a batch size of 8, along with a linear warmup and a cosine annealing schedule. Training spans 2 days on eight A6000 GPUs. Additional details on the tumor synthesis process during Segmentation Model training can be found in DiffTumor [14].

For inference, a sliding window strategy with 0.75 overlap is used. Tumor predictions that fall outside their corresponding organs are removed by post-processing with organ pseudo-labels obtained from previous research†.

B.4. Heuristic Function

We implement a CNN-based survival analysis model as Heuristic Function. The framework adopts 3D ResNet (MC3) as the backbone and Two-way Transformer as the interaction module of pre-treatment and post-treatment CT features. A multi-

*Cardoso *et al.* [12]: https://monai.io/

†Liu *et al.* [49, 50]: https://github.com/ljwztc/CLIP-Driven-Universal-Model

instance aggregator [60] with consecutive fully connected layers is utilized for survival risk scoring. It is implemented on PyTorch using 8 NVIDIA RTX A6000 GPUs. Their intensities are truncated to the range $[-175, 600]$ to maintain the discrimination of lipiodol/necrosis/viable areas, then linearly normalized to [-1, 1]. During training, $96 \times 96 \times 96$ patches are randomly cropped around either foreground or background voxels based on a set ratio. Each patch is subjected to a 90° rotation with probability 0.1 and an intensity shift of 0.1 with probability 0.2. To avoid confusing the left and right organs, mirroring augmentation is not used. We utilize the Adam optimizer with hyperparameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$, a learning rate of 0.00002, and a batch size of 5 per GPU. For the inference of each case, we predict the survival risk scores of 5 patches around the foreground and average them to obtain the final score.

C. Comparison against Multi-Modal GPTs

We carefully design prompt templates for multi-modal GPTs to generate TACE treatment protocol. The first template (Figure 11) is for our dataset with a larger action space, defining the task description, a predefined set of chemotherapy drugs and embolization materials, and an example of input-output in JSON format. The second template (Figure 12) is specifically designed for the HCC-TACE-Seg dataset, featuring a different selection of chemotherapy drugs and embolization materials. Both prompts instruct GPTs to analyze CT images and generate an appropriate TACE treatment plan, submitting results in JSON format with predefined keywords.

You are a radiation oncologist, please **list potential TACE drug and embolism sets** based on the patient's pre-treatment CT image. Please follow the below guidelines:

---

* * Task Description**

1. Analyze the input CT images and output potential TACE chemotherapy drug and embolization material sets for treatment. You can include any drugs and embolisms that you think may be helpful for the treatment. Chemotherapy drugs and embolization materials are limited to those in the Action Base.
2. The TACE action set is output in JSON format, including treatment plan keywords such as chemotherapy drugs and embolization materials.

Action Base

Chemotherapy Drugs

- Raltitrexed
- Epirubicin
- Oxaliplatin
- Lobaplatin
- Mitomycin
- Idarubicin
- Nedaplatin
- Pirarubicin
- Cisplatin
- Idarubicin
- THP
- Hydroxycamptothecin

** Embolization Materials **

- Lipiodol
- Gelatin Sponge
- PVA
- Absolute Alcohol
- NBCA
- KMG

Example

Input

{
"image": {image_property}
"patient_id": 001
}

Output

{
001: {
"Chemotherapy Drugs": "Raltitrexed; Lobaplatin; Oxaliplatin; Mitomycin; THP"
"Embolization Materials": "Lipiodol; Gelatin Sponge;PVA;NBCA"}
}

Figure 10. Policy model prompt template for our dataset.

You are a radiation oncologist, please design a TACE treatment plan based on the patient's pre-treatment CT image. Please follow the below guidelines:

###* * Task Description**
1. Analyze the input CT images and output the TACE treatment plan that you think is appropriate for the patient. The plan should include chemotherapy drugs and embolization materials that comply with clinical guidelines. Chemotherapy drugs and embolization materials are limited to those in the Action Set.
2. The TACE treatment plan is output in JSON format, including treatment plan keywords such as chemotherapy drugs and embolization materials.

Action Set
Chemotherapy Drugs
- Raltitrexed
- Epirubicin
- Oxaliplatin
- Lobaplatin
- Mitomycin
- Idarubicin
- Nedaplatin
- Pirarubicin
- Cisplatin
- Idarubicin
- THP
** Embolization Materials **
- Lipiodol
- Gelatin Sponge
- PVA
- Absolute Alcohol
- NBCA

Example
Input
{
"image": {image_property}
"patient_id": 001
}
Output
{
001: {
"keywords": "Raltitrexed; Lobaplatin; Lipiodol; Gelatin Sponge"}
}

Figure 11. VLM prompt template for our dataset.

You are a radiation oncologist, please design a TACE treatment plan based on the patient's pre-treatment CT image. Please follow the below guidelines:
---
* * Task Description**
1. Analyze the input CT images and output the TACE treatment plan that you think is appropriate for the patient. The plan should include chemotherapy drugs and embolization materials that comply with clinical guidelines. Chemotherapy drugs and embolization materials are limited to those in the Action Set.
2. The TACE treatment plan is output in JSON format, including treatment plan keywords such as chemotherapy drugs and embolization materials.

Action Set
Chemotherapy Drugs
- Mitomycin
- Doxorubicin
- Cisplatin
** Embolization Materials **
- Lipiodol
- LC Beads

Example
Input
{
"image": {image_property}
"patient_id": 001
}
Output
{
001: {
"keywords": " Doxorubicin; LC Beads"}
}

Figure 12. VLM prompt template for HCC-TACE-Seg.