Joint Prediction of Meningioma Grade and Brain Invasion via Task-Aware Contrastive Learning

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Abstract. Preoperative and noninvasive prediction of the meningioma grade is important in clinical practice, as it directly influences the clinical decision making. What’s more, brain invasion in meningioma (i.e., the presence of tumor tissue within the adjacent brain tissue) is an independent criterion for the grading of meningioma and influences the treatment strategy. Although efforts have been reported to address these two tasks, most of them rely on hand-crafted features and there is no attempt to exploit the two prediction tasks simultaneously. In this paper, we propose a novel task-aware contrastive learning algorithm to jointly predict meningioma grade and brain invasion from multi-modal MRIs. Based on the basic multi-task learning framework, our key idea is to adopt contrastive learning strategy to disentangle the image features into task-specific features and task-common features, and explicitly leverage their inherent connections to improve feature representation for the two prediction tasks. In this retrospective study, an MRI dataset was collected, for which 800 patients (containing 148 high-grade, 62 invasion) were diagnosed with meningioma by pathological analysis. Experimental results show that the proposed algorithm outperforms alternative multi-task learning methods, achieving AUCs of 0.8870 and 0.9787 for the prediction of meningioma grade and brain invasion, respectively. The code is available at https://github.com/IsDling/predictTCL.

Keywords: Meningioma grading · Brain invasion · Preoperative prediction · Contrastive learning · Feature disentanglement.

1 Introduction

Meningiomas are the most common primary intracranial tumors in adults, comprising 38.3% of central nervous system tumors [22]. According to the World Health Organization (WHO), meningiomas can be subdivided into three grades,
Fig. 1. MRI examples for low-grade meningiomas, high-grade meningiomas without/with brain invasion.

i.e., grade I (80%), grade II (18%) and grade III (2%). Grade I represents low-grade meningiomas, grade II and grade III are high-grade meningiomas. The WHO grading is an important factor in determining treatment options and overall prognosis for meningiomas. Specifically, low-grade meningiomas can be treated with surgery or beam radiation, and rarely recur after resection, while high-grade meningiomas should be treated with both means, and subjected to universal recurrence for grade III and 20–75% recurrence rates for grade II [5,13].

In another aspect, brain invasion is taken as a stand-alone pathological criterion for distinguishing between grade I and grade II in 2016 WHO classification [19]. Recent researches also uncover a link between brain invasion and increased risks of tumor progression, disease recurrence and poor prognosis [21,17].

In real clinical diagnosis, pathological analysis provides the gold standard for the determination of brain invasion and meningioma grading [18,19]. However, to conduct pathological analysis, clinicians are required to sample tissues from the core and surrounding areas of the tumor during invasive resection or biopsy, while some important treatment decision has been made without the knowledge of brain invasion and meningioma grading. Moreover, the accuracy of brain invasion determination heavily depends on the clinician’s experience [29]. If the brain tissue samples do not fall in the invasion area, there is a risk that the patient will be misdiagnosed and his prognosis can be affected. Given these practical concerns, accurate preoperative and non-invasive assessment of meningioma grade and brain invasion is clinically essential to facilitate treatment decisions.

Many recent studies in the clinical field are devoted to predicting the grade of meningioma or identification of brain invasion by analyzing brain MRIs [10,23,31,11,28,15,29]. Hale et al. extracted radiographic features by traditional statistical methods and verified that machine learning-based methods can help to predict meningioma grade [10]. Later on, several followed-up studies are reported to extract different hand-crafted features or CNN features and then use machine learning-based classifiers, such as SVM or random forest, to predict the meningioma grade [23,31,11], or for the determination of brain invasion [15,29]. Moreover, Zhang et al. applied the widely-used deep-learning network, ResNet, to predict the meningioma grade [28]. Overall, most of the previous studies extracted hand-crafted features and conducted the two tasks, without exploring the powerful feature representation learning of neural networks. Furthermore, to the best of our knowledge, there is no previous study performing both tasks simultaneously, although there exist clinical connections between them.
In this paper, as a preliminary exploration, we develop a novel multi-task learning algorithm to make joint prediction of brain invasion and meningioma grade from multi-modal MRIs, including post-contrast T1-weighted (T1C), contrast T2 fluid attenuation inversion recovery (FLAIR-C), and apparent diffusion coefficient (ADC) images, following clinical practice (Fig. 1). Note that the common multi-task learning strategy adopts a shared backbone and then learns task-specific features with multiple heads to perform separate tasks [9]. Existing methods are usually focused to tune the loss function to balance contributions between different tasks [8,16], which is still weak to ensure the feature representation ability. We notice that multi-task methods assume that the tasks are related to each other, and considering tasks simultaneously can help to improve the feature representation ability. Hence, in our work, we propose a novel task-aware contrastive learning strategy, by respecting both the coherence between tasks and the distinctness of each individual task. Our approach disentangles the multi-modal MRI features into task-specific features, which are sensitive to a certain classification task, as well as task-common features that are helpful to both prediction tasks. Then we align the task-common features to each task, and enforce the feature emeddings contributing to the same task to be more similar than the embeddings contributing to different tasks, via contrastive losses.

In summary, our contributions are three folds: (1) This is the first study to simultaneously predict meningioma grade and identify brain invasion. (2) We propose a simple yet effective task-aware contrastive learning strategy, which derives task-common features in addition to task-specific features from the shared feature encoder, and takes task-common features as a guidance to improve the prediction ability for both tasks; (3) Experiments on our own collected dataset demonstrate that the proposed approach can accurately predict meningioma grade and brain invasion, and outperforms alternative methods effectively.
2 Method

Fig. 2 demonstrates the architecture of the proposed multi-task framework. Given multi-modal brain images, we apply multiple backbones to extract the feature maps from MRIs respectively, and here ResNet34 is adopted as the backbone. The fused features from multiple backbones contain rich information for performing multiple tasks. We then disentangle the fused feature maps to task-specific features and task-common features, and a new task-aware contrastive learning strategy is leveraged to exploit the “comparative” relation between task-specific features and task-common features.

2.1 Feature Disentanglement

As demonstrated by [6,7], the disentangled representation, which decouples the entangled features into task-specific features that are easier to predict, is beneficial to the realization of multi-task learning. Like most multi-task applications, our goal is to find the most discriminative features for each prediction task. Although the general practice is to disentangle the fused features into multiple task-specific features, we consider that there are features that are simultaneously effective for multiple tasks, since multi-task learning assumes that the tasks are related to each other. In our work, we disentangle the fused features into the task-specific feature for invasion identification task (denoted as $G_i$), the task-specific feature for meningioma grading task ($G_m$), and the task-common feature ($G_c$). Here, we adopt a convolution layer and an average pooling to realize feature disentanglement, which is formulated as follows,

$$G_k = AP(Conv(Concat(F_T, F_F, F_A))), k = i, m, c,$$

where {$F_T, F_F, F_A \in \mathbb{R}^{C \times h \times w \times d}$} denote the feature maps extracted from T1C, Flair-C and ADC MRIs respectively, and their sizes are all $512 \times 4 \times 4 \times 8$. $Concat(\cdot)$ means channel concatenation. $Conv(\cdot)$ means $2 \times 2$ convolution operation, $AP(\cdot)$ is average pooling. After flattening, the resultant disentangled features {$G_i, G_m, G_c$} are feature vectors with size of 512. Note that to realize feature disentanglement, we will rely on the task-aware contrastive learning as well as auxiliary classification branches, discussed in the following subsections.

2.2 Task-Aware Contrastive Learning

The proposed task-aware contrastive learning strategy has two functions, one is to help feature disentanglement, and the other is to improve the predictive ability of each task-specific features for the corresponding task by leveraging the relationship between task-common features and task-specific features. Contrastive learning (CL) has shown great potential in the natural image field, and has been applied in the medical image field in recent years. Its core idea is “learn to compare”: given an anchor point, distinguish a similar (or positive) sample from a set of dissimilar (or negative) samples, in a projected embedding space [25]. Most
current CL researches are image-level and pixel-level. Image-level CL \cite{12,26} takes multiple views of the same image as positive samples and different images as negative samples. Pixel-level CL \cite{25,27} take pixels from the same class as positive samples and pixels from different classes as negative samples. Different from CL methods mentioned above, we propose a new task-aware contrastive learning strategy. As the task-common feature is supposed to be helpful for both tasks, we align it to each task and enforce the feature embeddings contributing to the same task to be more similar than the embeddings contributing to different tasks, via contrastive losses. This simple strategy respects the coherence between tasks and strengthens the distinctness of each individual task, thus improving the feature representation ability of the network.

Taking the invasion identification task as an example, we align the task-common feature $G_c$ to this task to get $G_{c,i}$ via a fully connected layer, yielding $G_{c,i} \in \mathbb{R}^{128}$. Then $G_{c,i}$ is expected to be similar to the task-specific feature for invasion identification $G_i$, and not like the task-specific feature for meningioma grading $G_m$. To this end, we also transform two task-specific features into $\hat{G}_i$ and $\hat{G}_m$ via fully connected layers, respectively, where $\hat{G}_i, \hat{G}_m \in \mathbb{R}^{128}$. We define the task-aware contrastive loss for the invasion identification task as

$$L_{\text{con-inv}} = -\log \frac{\exp(\text{sim}(G_{c,i}, \hat{G}_i)/\tau)}{\exp(\text{sim}(G_{c,i}, G_i)/\tau) + \exp(\text{sim}(G_{c,i}, \hat{G}_m)/\tau)},$$

(2)

where $\text{sim}(\cdot)$ denotes cosine similarity between two feature vectors; $\tau$ is the temperature parameter and set as 0.07 empirically. Similarly, the task-aware contrastive loss for the meningioma grading task is defined as follows,

$$L_{\text{con-men}} = -\log \frac{\exp(\text{sim}(G_{c,m}, \hat{G}_m)/\tau)}{\exp(\text{sim}(G_{c,m}, \hat{G}_m)/\tau) + \exp(\text{sim}(G_{c,m}, G_i)/\tau)},$$

(3)

where $G_{c,m} \in \mathbb{R}^{128}$ denotes the manipulated feature vector via aligning the task-common feature $G_c$ to meningioma grading.

### 2.3 Overall Loss Functions and Training Strategy

Besides to estimate the task-aware contrastive losses, the features for the same task are further concatenated and undergo a three-layer MLP (with dimensions of 256, 32 and 2), yielding the prediction loss for this task, i.e. $L_{\text{cls-inv}}$ and $L_{\text{cls-men}}$. In order to promote the guiding ability of task-common features, we introduce auxiliary classification branches to the disentangled task-specific features; see Fig. 2 which offers two auxiliary classification losses, i.e. $L_{\text{aux-inv}}$ and $L_{\text{aux-men}}$. Each auxiliary branch is a four-layer MLP with dimensions of 512, 256, 32 and 2. In summary, our multi-task learning loss is defined as

$$L = L_{\text{cls-inv}} + L_{\text{cls-men}} + \alpha(L_{\text{con-inv}} + L_{\text{con-men}}) + \beta(L_{\text{aux-inv}} + L_{\text{aux-men}}).$$

(4)

We use cross entropy loss as the classification loss; $\alpha$ and $\beta$ are weights to balance the contribution of different losses, which are set as 1 and 0.7 empirically. Besides,
Table 1. Details of the dataset.

| Characteristics | Low grade |       | High grade |       |
|-----------------|-----------|-------|------------|-------|
|                 |           | invasion | noninvasion |       |
| Number          | 652       | 62     | 86         |       |
| Age (years ± SD)| 56.75 ± 10.7| 55.77 ± 11.97 | 55.52 ± 12.46 |       |
| Male            | 139       | 26     | 39         |       |
| Female          | 513       | 36     | 47         |       |

to ensure the contrastive learning strategy work well, we add the contrastive
learning loss after a period of training, empirically set as 30 epoches.

3 Experiments

Dataset and Preprocessing. We collected an MRI dataset of meningiomas
for patients with tumor resection between March 2016 and March 2021 in Brain
Medical Center of Tianjin University, Tianjin Huanhu Hospital. MRI scans were
performed with four 3.0T MRI scanners (i.e., Skyra, Trio, Avanto, Prisma from
Siemens). Table 1 presents details of the dataset, which contains 800 MRI vol-
umes with a size of $256 \times 256 \times 24$ and 1mm spacing. Every MRI volume contains
three modals, i.e., T1C (contrast-enhanced T1), FLAIR-C (contrast-enhanced
T2 FLAIR) and ADC, and has two labels (i.e., grading and invasion classification
labels) for each patient.

During experiments, due to the small amount of invasion samples, we use
randomly drawn data division to alleviate overfitting. Specifically, we randomly
draw training and testing sets in three runs to ensure training and testing sets
have similar distribution of low/high, invasion yes/no. Then there are 214 MRIs
for training and the remaining MRIs as the testing dataset in each run. Specific-
ally, the training dataset contains 44 invasion MRIs and 170 noninvasion MRIs,
69 high grade MRIs and 145 low grade MRIs. For preprocessing, radiologists
are asked to crop the tumor ROIs following previous works [1, 14, 2]. In order
to maintain the shape of tumor and edema area, we zero pad the cropped image
into a square and resize them into $128 \times 128 \times 24$ as the network input.

Evaluation Metrics and Implementation Details. The metrics used to eval-
uate the network performance are Sensitivity, Specificity, Accuracy, G-Means,
Balanced Accuracy [3], MCC, AUPRC, and AUC. Also note that MCC and
AUPRC are two metrics which can be used with imbalanced datasets. The pro-
posed algorithm is built with PyTorch on a NVIDIA RTX 3090 GPU. We use the
Adam optimizer and set the initial learning rate to $1e^{-3}$. To prevent overfitting,
we add dropout of 0.5 and $L2$ regularization with regularization parameter as
$1e^{-3}$. Flip, Gaussian noise and random crop are employed in data augmenta-
tion. Our model has a parameter size of 200M, trained with 100 epoches, and
takes an average inference time of 0.098s for one image.

Comparison with Other Methods. As there are no existing methods directly
available for our joint classification tasks, we built four alternative methods for
Table 2. Quantitative comparison. The best and second best results for each metric are highlighted in red and blue, respectively.

| Methods | Invasion | Meningioma |
|---------|----------|------------|
|         | Sensitivity | EFMT 0.7593 | MFMT 0.6852 | MMoE 0.7963 | MAML 0.7407 | Proposed 0.7593 |
|         | Specificity 0.9707 | 0.9771 | 0.9630 | 0.9824 | 0.9789 |
|         | Accuracy 0.9642 | 0.9681 | 0.9579 | 0.9750 | 0.9721 |
|         | G-Means 0.8555 | 0.8181 | 0.8756 | 0.8529 | 0.8619 |
|         | Balanced Accuracy 0.8650 | 0.8312 | 0.8797 | 0.8616 | 0.8691 |
|         | MCC 0.5787 | 0.5691 | 0.5529 | 0.6486 | 0.6252 |
|         | AUPRC 0.3607 | 0.3558 | 0.3329 | 0.4490 | 0.4157 |
|         | AUC 0.9574 | 0.9527 | 0.9425 | 0.9668 | 0.9787 |

comparison. All the compared methods use ResNet34 as the backbone, and are trained on the collected dataset to get best results. (1) EFMT (Early Fusion with Multi-task). We built a model that concatenates multi-modal MRIs at the input and the extracted features are connected to two classifiers that perform the corresponding tasks. (2) MFMT (Middle Fusion with Multi-task). The MFMT model contains three ResNet34 to extract the features of multi-modal MRIs respectively, and the concatenated features are fed to two classifiers to finish both tasks. (3) MMoE [20]. We adapt this method to our multi-task topic, which uses three expert networks and two gating networks to generate task-specific features. We adopt ResNet34 as the expert network and ResNet18 as the gating network. (4) MAML [30]. This method extracts features for each modality via multiple encoders, and estimates an modality-aware attention map to obtain boosted features. We change the output of this method to two classifiers. It is noted that the classifier adopted in the above compared methods is the same as the auxiliary branch in our proposed framework; see Fig. 2.

Table 2 summarizes the comparison results. Among the compared methods, for the brain invasion identification task, MMoE gets the highest sensitivity, g-means, and balanced accuracy (0.7963, 0.8756, 0.8797). MAML achieves the best specificity, accuracy, MCC, AUPRC, and AUC (0.9824, 0.9750, 0.6486, 0.4490, 0.9668). For the meningioma grade prediction task, MAML gets the best sensitivity (0.6920) and MFMT achieves the best specificity, accuracy, g-means, balanced accuracy, MCC, AUPRC, and AUC (0.9132, 0.8788, 0.7748, 0.7493, 0.5327, 0.4088, 0.8701). In comparison, our proposed algorithm achieves the best AUC (0.9787, 0.0119 better than the MAML) for the brain invasion identification task; and the best specificity, accuracy, g-means, balanced accuracy, MCC,
Table 3. The results of ablation experiments. TC, Aux and $L_{con}$ mean Task-common branch, auxiliary branch and contrastive loss respectively. The best and second best results for each metric are highlighted in red and blue, respectively.

| Ablation | Baseline | Baseline1 | Baseline2 | Baseline3 | Baseline4 | Proposed |
|----------|----------|-----------|-----------|-----------|-----------|----------|
| TC       | ×        | ✓         | ✓         | ✓         | ✓         | ✓        |
| $L_{con}$ | ×        | ×         | ✓         | ×         | ✓         | ✓        |
| Aux      | ×        | ×         | ×         | ✓         | ✓         | ✓        |

**Invasion**

| Metric         | Baseline | Baseline1 | Baseline2 | Baseline3 | Baseline4 | Proposed |
|----------------|----------|-----------|-----------|-----------|-----------|----------|
| Sensitivity    | 0.6111   | 0.7778    | 0.7407    | 0.7037    | 0.7593    |          |
| Specificity    | 0.9730   | 0.9736    | 0.9783    | 0.9794    | 0.9789    |          |
| Accuracy       | 0.9619   | 0.9676    | 0.9710    | 0.9710    | 0.9721    |          |
| G-Means        | 0.7629   | 0.8699    | 0.8504    | 0.8291    | 0.8619    |          |
| Balanced Accuracy | 0.7921 | 0.8757    | 0.8595    | 0.8416    | 0.8691    |          |
| MCC            | 0.5379   | 0.5990    | 0.6097    | 0.5974    | 0.6252    |          |
| AUPRC          | 0.3216   | 0.3859    | 0.4026    | 0.3882    | 0.4157    |          |
| AUC            | 0.9542   | 0.9695    | 0.9727    | 0.9717    | 0.9787    |          |

**Meningioma**

| Metric         | Baseline | Baseline1 | Baseline2 | Baseline3 | Baseline4 | Proposed |
|----------------|----------|-----------|-----------|-----------|-----------|----------|
| Sensitivity    | 0.5781   | 0.6878    | 0.7131    | 0.6962    | 0.6878    |          |
| Specificity    | 0.9211   | 0.8941    | 0.8692    | 0.8988    | 0.9277    |          |
| Accuracy       | 0.8749   | 0.8663    | 0.8481    | 0.8714    | 0.8953    |          |
| G-Means        | 0.7240   | 0.7841    | 0.7859    | 0.7909    | 0.7981    |          |
| Balanced Accuracy | 0.7486 | 0.7289    | 0.7070    | 0.7336    | 0.7806    |          |
| MCC            | 0.4934   | 0.5157    | 0.4903    | 0.5272    | 0.5860    |          |
| AUPRC          | 0.3728   | 0.3935    | 0.3676    | 0.4016    | 0.4599    |          |
| AUC            | 0.8851   | 0.8753    | 0.8853    | 0.8815    | 0.8870    |          |

AUPRC, and AUC (0.9277, 0.8953, 0.7981, 0.7806, 0.5860, 0.4599, 0.8870) for the meningioma grade prediction task. It is noted that for MCC and AUPRC metrics, our method reports the best results for meningioma grade prediction and the second best results for brain invasion identification. The standard deviations of metrics results can be found in the supplementary material. We also calculate AUC differences between compared methods and ours using ROC-kit [24], while p-values are less than 0.05.

**Ablation Analysis.** To demonstrate the effectiveness of the TC (Task-common branch), Aux (auxiliary branch) and $L_{con}$ (contrastive learning loss), we conduct ablation studies; see Table 3. Compared with the proposed algorithm, Baseline1 removes the task-common branch, auxiliary branch and contrastive learning loss. Baseline2 adds the task-common branch, while Baseline3 and Baseline4 add auxiliary branch and contrastive learning loss, respectively.

It can be seen from the first two columns that MCC and AUPRC increase from (0.5379, 0.3216) to (0.5590, 0.3859) for invasion task and from (0.4934, 0.3728) to (0.5157, 0.3935) for meningioma task by adding TC, which proves the rationality of the task-common branch. On this basis, $L_{con}$ is added and improves MCC and AUPRC to (0.6097, 0.4026) for invasion task. What’s more, respecting the Baseline3, the proposed method adds $L_{aux}$ to further improve MCC and AUPRC to (0.6252, 0.4157) for invasion task and (0.5860, 0.4599) for meningioma task, which verifies that the auxiliary branch can help the contrastive learning.
strategy to play a better role. In comparison, the sensitivity of meningioma grade is somehow lower, for which we would like to further explore in the future work.

4 Conclusion

Joint prediction of brain invasion and meningioma grade is a novel topic and an urgent clinical need. As far as we know, there is no study so far that solves both prediction tasks based on brain MRIs simultaneously. In this paper, we propose a novel contrastive learning-based multi-task algorithm, which respects the coherence between tasks and also enhances the distinctness of each individual task. We first use a middle-fusion strategy to fuse the feature maps from the multi-modal MRIs. Then, we disentangle the fused image features into task-specific features, which focus on a separate task, and task-common features that can perform both tasks. A new contrastive loss is leveraged to use task-common features as guidance to improve the prediction ability of two tasks. In the future work, we would like to explore the influence of each modality MRI on the two tasks to further improving the results of both tasks.

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