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Combining radiomics and convolutional neural network to predict tumor growth of vestibular schwannoma

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INTRODUCTION

Vestibular schwannoma (VS) is the most common extra-axial benign tumor in the posterior fossa of adults. In the management of patients with VS, knowledge of tumor growth behavior is crucial to determine the appropriate follow up interval and when should the therapeutic intervention be performed. In the current clinical practice, tumor growth is determined through measuring the change in tumor volume or the greatest tumor linear dimension on serial MRI imaging with a fixed interval, which may lead to delayed treatment for fast-growing tumors or over-imaging for slow-growing tumors. To avoid unnecessary imaging surveillances for patients having stable VS and identify VS patients at risk of fast tumor growth in early stage, we proposed a hybrid predictive model for VS growth prediction based on MR images acquired at the initial scan. To take advantages of both hand-crafted features and learning-based features, we designed a multi-objective multi-classifier radiomics (MOCR) model and a 2D convolutional neural network (CNN) for the prediction. The final prediction was obtained by fusing probability outputs of MOCR and CNN through an evidential reasoning (ER) approach. The developed model will aid in personalized management of patients with VS.

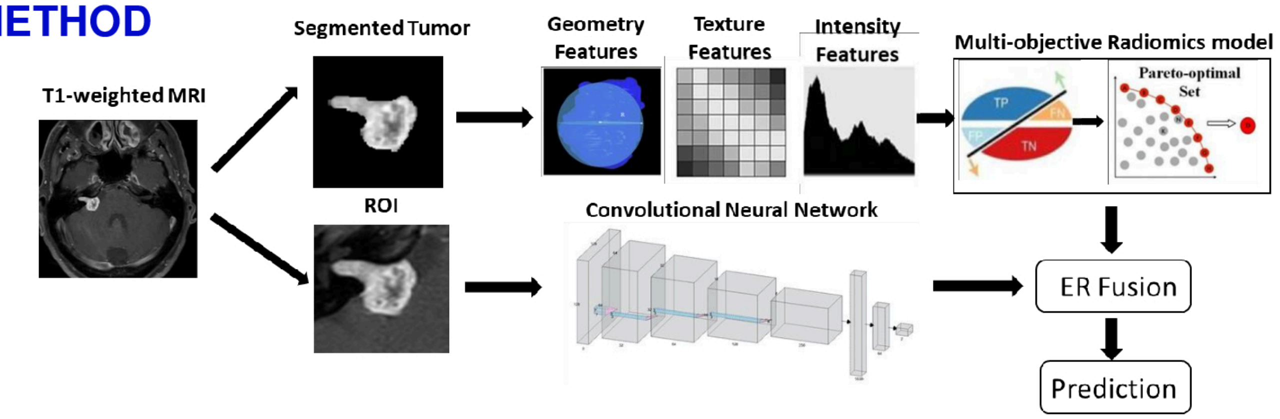
AIM

In this work, we aim to develop a hybrid predictive model to predict VS tumor growth based on the initial diagnosis imaging of the tumor to aid in personalized management of VS.

DATASET

65 VS patients from our institute were included in this study. Each patient has two contrast-enhanced T1-weighted MRI scans with a median interval of 7.8 months (6.4-12.9). Tumors were manually segmented by two observes. Based on their segmentations, 36 of these patients were determined to have tumor growth, which was defined as an increase above 20% volumetrically between the two consecutive scans.

METHOD



We performed MRI image standardization and resampled images to have the same in-plane resolution before feature extraction and model training. Since most of the tumors only present on a single MRI slice, for training of the MOCR model, we extract 217 2D radiomics features, comprising 9 intensity features, 8 geometry features and 200 texture features for each patient. Before model training, we used the minimal-redundancy-maximal-relevance criterion (mRMR) method for feature pre-selection, and 50 features was pre-selected for model training. synthetic minority oversampling technique (SMOTE) was used to oversample the radiomics features non-growth samples and produce class-balanced training dataset. In the MOCR model, sensitivity and specificity were simultaneously used as the objective functions for model optimization. Three classifiers, support vector machine (SVM), logistic regression (LR) and discriminant analysis (DA), were used together to construct the multi-classifier model. An immune algorithm was used for radiomics feature selection and model parameter training.

To train the CNN model, we extracted a patch of size 128×128, which included the tumor and its surrounding pixels for each patient. In the CNN model, we modified AlexNet as the model structure, Adam algorithm as the optimizer, and weighted binary cross entropy as the loss function. Image shift and random noising were used for data augmentation.

After model training, the final output probabilities of testing samples were calculated through ER fusion of the output probabilities from the MOCR model and CNN model. Weighting factors of each model for ER fusion were calculated based on the model performance on the validation dataset.

RESULTS

Five-fold cross-validation was adopted for model training, validation and testing. Sensitivity, specificity, accuracy and area under the receiver operating characteristic curve (AUC) of the prediction results on testing samples of the hybrid model are 0.75, 0.76, 0.75 and 0.80, respectively, which are all higher than MOCR- and CNN-based model alone. The sensitivities and specificities of MOCR model and hybrid model are more balanced than those of CNN model given this unbalanced and small-size dataset.

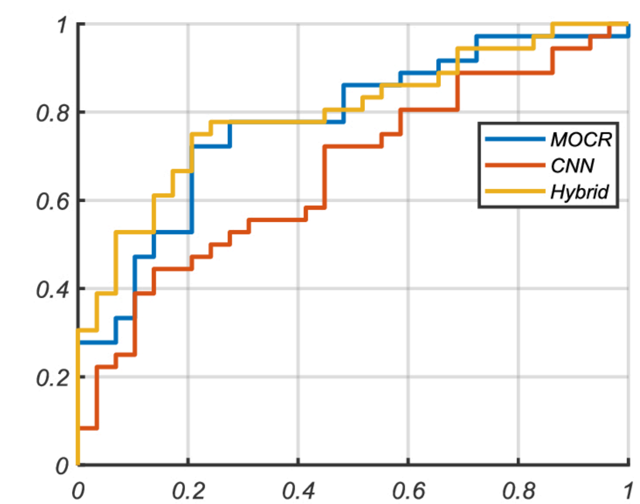


Figure 1. ROC Curve of tumor growth prediction models.

Model	Sensitivity	Specificity	Accuracy	AUC
MOCR	0.72	0.72	0.72	0.78
CNN	0.72	0.55	0.65	0.66
Hybrid	0.75	0.76	0.75	0.80

Table 1. Results of tumor growth prediction models.

CONCLUSIONS

We developed a hybrid model which combined convolutional neural network and multi-objective radiomics model for early stage VS tumor growth prediction using the initial diagnosis MRI image. In the hybrid model, the fusion of the output probabilities of MOCR model and CNN model improved the prediction reliability.

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