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Glioma Tumor Grading using Synergic Deep Learning Model

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Introduction

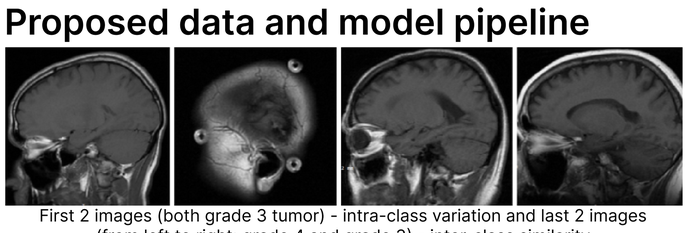
- Deep learning has improved medical imaging for tumor grading, yet the progress has been limited due to overfitting, and the challenges posed by inter-class similarity and intra-class variation.
- We propose a Synergic Deep Learning model for automatic grading of glioma tumors, where the SDL architecture enables two DCNNs to mutually learn from each other.
- The SDL model achieves an accuracy of 98.36% and outperforms popular pre-trained models in terms of testing accuracy, recall, and F1 score.

Contributions

- A Synergic Deep Learning model with an AlexNet backbone fine-tuned for T1-weighted sagittal tumor MRI slices.
- Comparison with popular state-of-the-art pre-trained models and results showing that the proposed model outperforms them for grading glioma tumors.
- A first-of-its-kind open-source implementation of the Synergic Deep Learning model.
- Discussions on the REMBRANDT dataset, stability interval of lambda, Gaussian filters for preprocessing brain MRI slices.

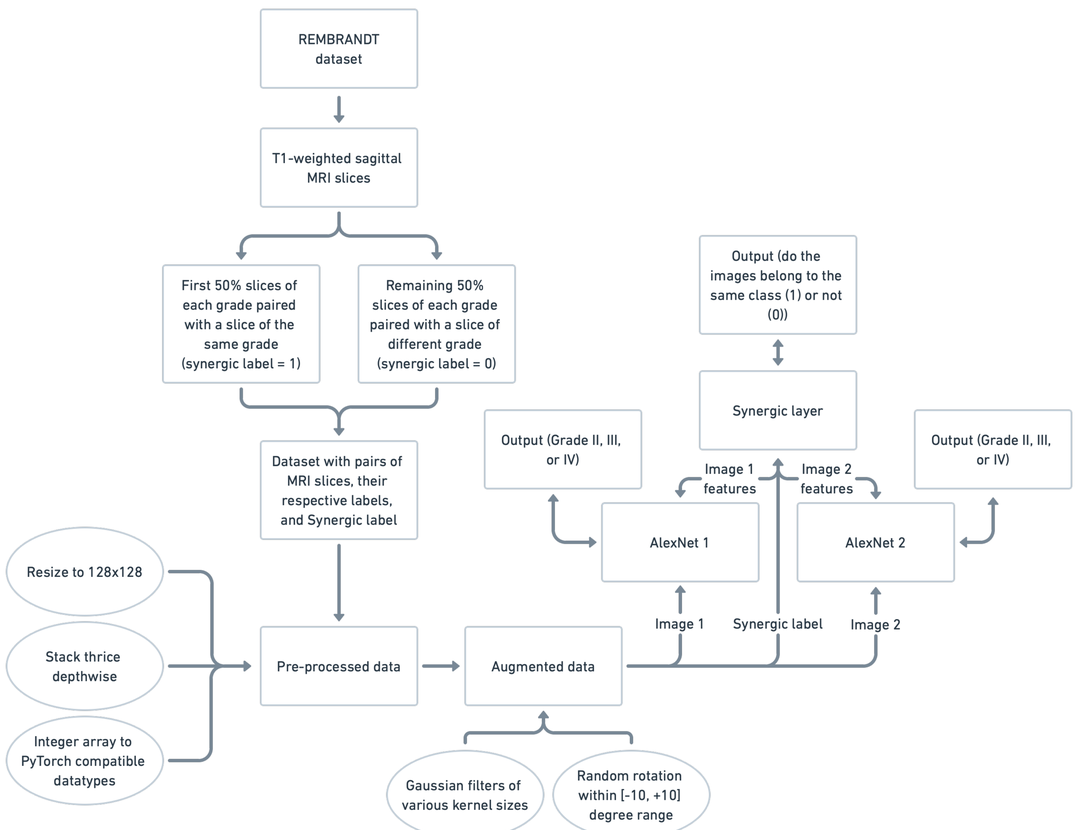
Proposed work

Proposed data and model pipeline

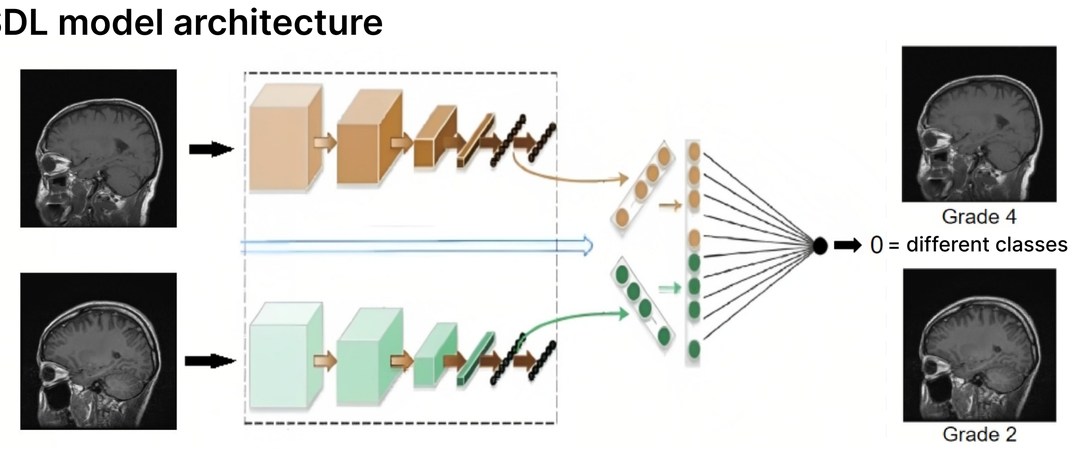


First 2 images (both grade 3 tumor) - intra-class variation and last 2 images (from left to right: grade 4 and grade 3) - inter-class similarity

Grade	Patients	Slices
2	7	128
3	6	108
4	7	181
Total	**20**	**417**



SDL model architecture



Training algorithm

$$f_{SDL} \leftarrow f_1 \cdot f_2$$

$$P_{SDL} \leftarrow SDL(f_{SDL})$$

$$loss_{DCNN_1} \leftarrow CE(P_1, y_1)$$

$$loss_{DCNN_2} \leftarrow CE(P_2, y_2)$$

$$loss_{SDL} \leftarrow BCE(P_{SDL}, y_{SDL})$$

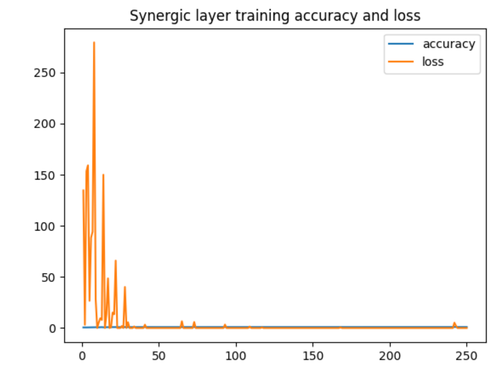
$$\Theta_{DCNN_1} \leftarrow \Theta_{DCNN_1} - \eta \times \left(\frac{\partial loss_{DCNN_1}}{\partial \Theta_{DCNN_1}} + \lambda \times \frac{\partial loss_{SDL}}{\partial \Theta_{SDL}}\right)$$

$$\Theta_{DCNN_2} \leftarrow \Theta_{DCNN_2} - \eta \times \left(\frac{\partial loss_{DCNN_2}}{\partial \Theta_{DCNN_2}} + \lambda \times \frac{\partial loss_{SDL}}{\partial \Theta_{SDL}}\right)$$

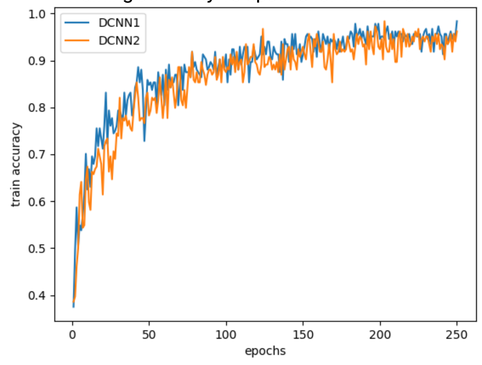
$$\Theta_{SDL} \leftarrow \Theta_{SDL} - \eta \times \frac{\partial loss_{SDL}}{\partial \Theta_{SDL}}$$

Results

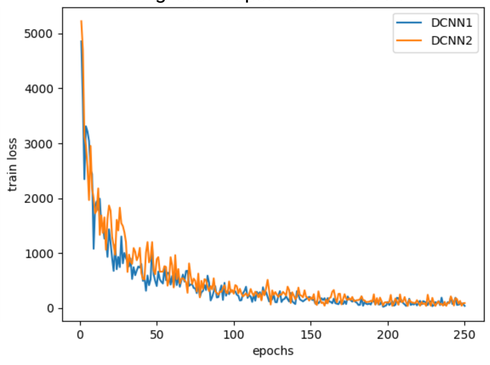
Model	Training Accuracy	Testing Accuracy	Precision	Recall	F1 score
Proposed SDL model	98.36	**92.85**	89.80	**92.3**	**90.91**
VGG19	**100**	69.05	66.67	66.67	66.50
AlexNet	**100**	78.57	77.15	74.44	75.10
ResNet50	**100**	89.88	**92.92**	87.04	88.75
ResNet152	**100**	90.48	91.11	89.44	89.76



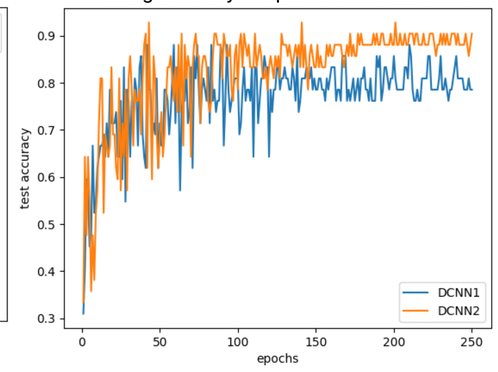
Training accuracy vs epochs for the 2 DCNNs



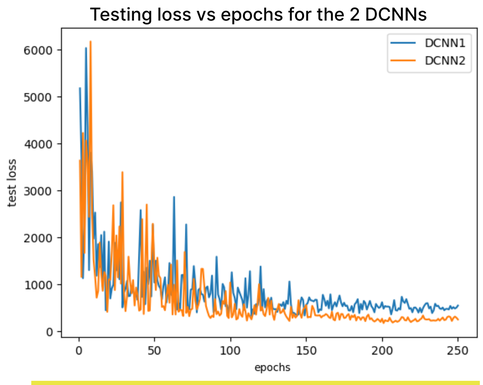
Training loss vs epochs for the 2 DCNNs



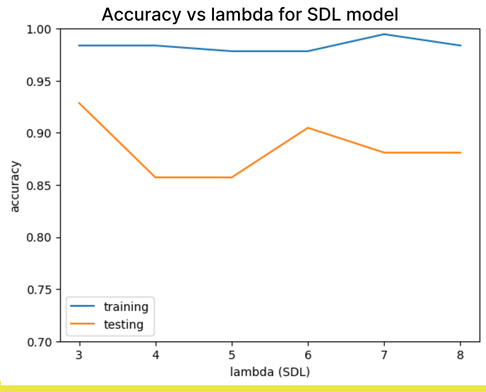
Testing accuracy vs epochs for the 2 DCNNs



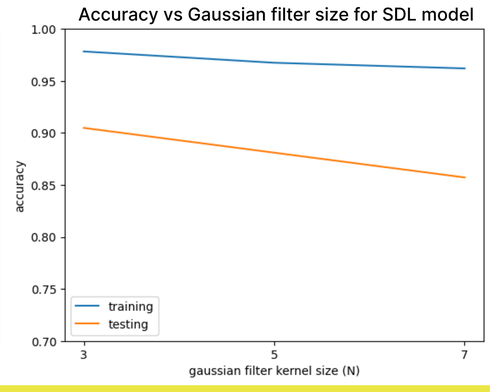
Testing loss vs epochs for the 2 DCNNs



Accuracy vs lambda for SDL model



Accuracy vs Gaussian filter size for SDL model



Discussion

- Selected only sagittal MRI slices as axial slices were noisy and tumor-less.
- Selected AlexNet as the backbone to minimize bias-variance tradeoff.
- AlexNet performed poorly but performed very well when used within SDL.
- Gaussian filters deteriorated the accuracies, proportional to the kernel size.
- Training accuracy stayed almost same but testing accuracy dropped while varying lambda within the stable interval.

Conclusions

We proposed a Synergic Deep Learning model with an AlexNet backbone for automated grading of glioma tumor MRI scans to overcome - 1. Overfitting, and 2. Significant inter-class similarity and intra-class variation.

The SDL model achieved the highest training accuracy of 99.45% at lambda =7 and the highest testing accuracy of 92.85% at lambda = 3.

The best SDL model gave us a precision of 89.80%, a recall of 92.3%, and an F1 score of 90.91%, outperforming VGG19, AlexNet, ResNet50, and ResNet152 in terms of testing accuracy, recall, and F1 score.

Future work

- Generalising the SDL model to SDL^n model.
- Joint segmentation classification SDL model for brain MRI scans.
- Include a refined dataset of axial MRI scans to learn features from two angles.
- RL to automatically select the best value of the synergic hyperparameter.

References

1. Zhang J, Xie Y, Wu Q, Xia Y. Medical image classification using synergic deep learning. Med Image Anal. 2019 May;54:10-19. doi: 10.1016/j.media.2019.02.010. Epub 2019 Feb 18. PMID: 30818161.
2. Zhang, J., Xie, Y., Wu, Q., Xia, Y. (2018). Skin Lesion Classification in Dermoscopy Images Using Synergic Deep Learning. In: Frangi, A., Schnabel, J., Davatzikos, C., Alberola-López, C., Fichtinger, G. (eds) Medical Image Computing and Computer Assisted Intervention – MICCAI 2018. MICCAI 2018. Lecture Notes in Computer Science(), vol 11071. Springer, Cham.