READING THE BRAIN:

USING MRIS FOR EARLY DETECTION OF DYSLEXIA

INTRODUCTION

What is Dyslexia?

- **Dyslexia** is a **learning disorder** characterized by difficulty **reading**
- 1in 10 Americans is **dyslexic** (to varying degrees) **[5]**
- **Early detection** and intervention can **reduce** the percentage of children reading below average level by **33% [7]**

Project Origin

Characters in Percy Jackson (childhood favorite book) had dyslexia

Wanted to help dyslexic children get the right support to learn to read

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Project Origin

Interested in neuroscience and AI, learned more from summer classes

Realized I could apply that knowledge to this problem

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Engineering Goal

Build AI model for dyslexia detection in children before reading age

Use 3D anatomical MRIs for earlier detection

CURRENT METHODS

Standardized test

1. Background Information
2. Oral Language Skills
3. Word Recognition
4. Spelling
5. Reading Comprehension
6. Vocabulary Knowledge

Neural imaging

Functional MRIs (fMRIs):
- ML model only achieves 72.7% accuracy and 60% precision **[13]**

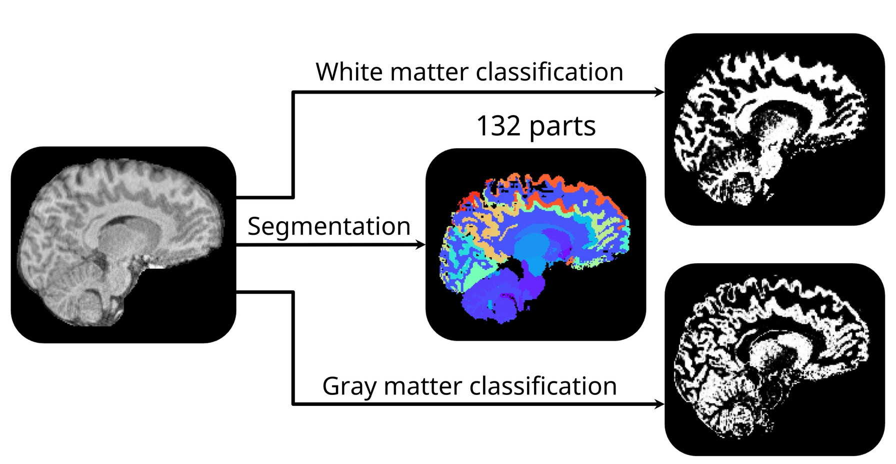
Anatomical MRIs:
- Volume of pars triangularis gray matter - biomarker of dyslexia **[3]**
- Found by expert humans manually inspecting brain scans

Limitations

- **All parts** of the brain are not fully explored
- Both fMRI and standardized tests require **active participation**
- Child must be of **reading age** for **both methods**

PREPROCESSING

Datasets			
Data source (study)	**Age**	**# Typical**	**# Dyslexic**
Reading-related functional activity in children with isolated spelling deficits and dyslexia **[1]**	8-10	22	20
Atypical Hemispheric Re-Organization of the Reading Network in High-Functioning Adults with Dyslexia: Evidence from Representational Similarity Analysis **[2]**	20-29	20	20



Pretrained MONAI model for **3D brain segmentation [12]**

132 parts identified

HMRF (Hidden Markov Random Field) **tissue classifier** from dipy library in python

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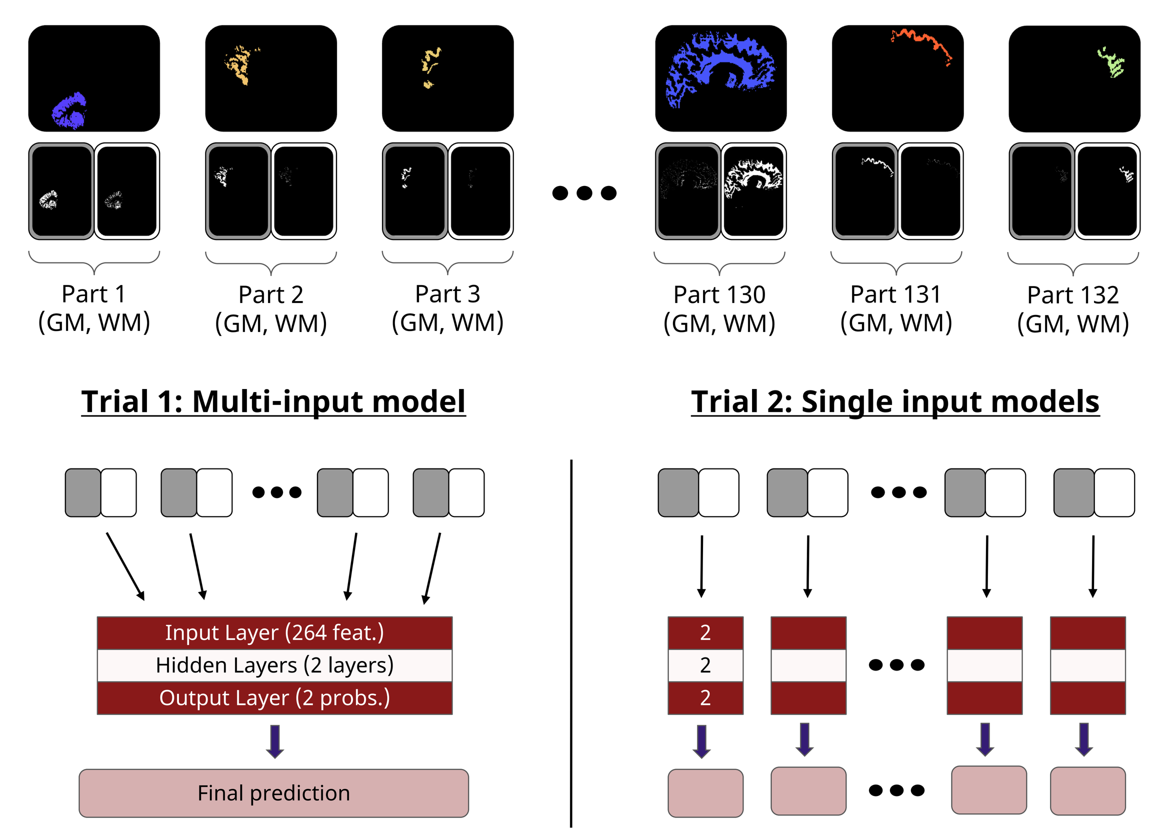
METHODS AND RESULTS

SINGLE-TIER



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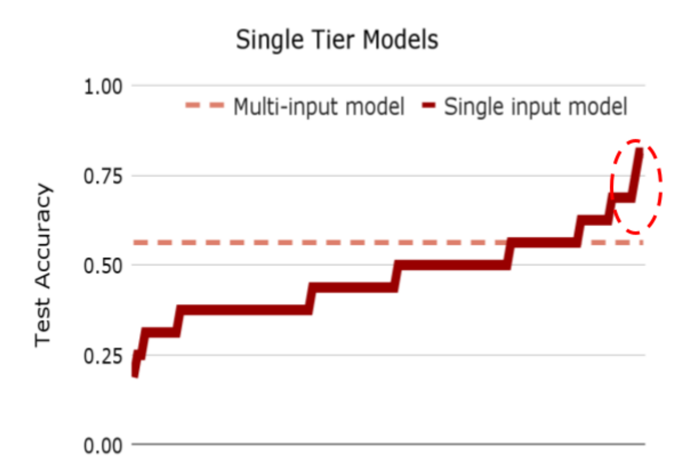

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Trial 1: Multi-input model
- Too many features
- Low accuracy (56.25%)

Trial 2: Single input model
- Too little data per model
- Higher accuracy (81.25%)

Key insight

Best single input models >> one multiple input model

Brain Part Analysis					
Part #	**Part name**	**Primary function**	**Train acc.**	**Test acc.**	**Train x test**
76	Left medial orbital gyrus	Decision-making, motivation	0.758	0.813	0.616
106	Left posterior orbital gyrus	Emotional response and reward	0.694	0.813	0.564
49	Right entorhinal area	Memory, spatial navigation	0.806	0.688	0.554
60	Left inferior occipital gyrus	Visual processing	0.742	0.688	0.510
130	Pars triangularis	Language processing and translation	0.710	0.688	0.488

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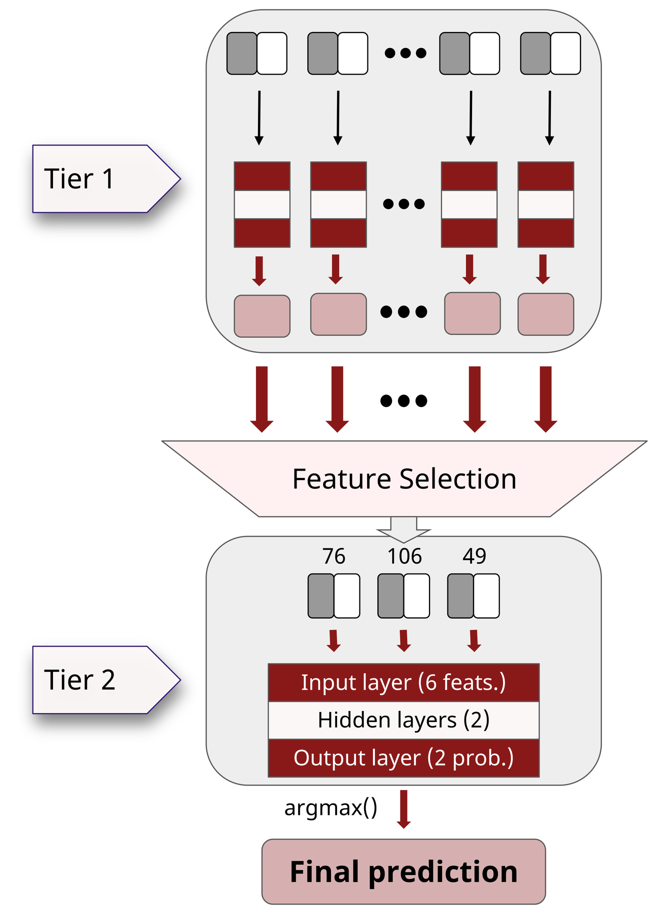
TWO-TIER



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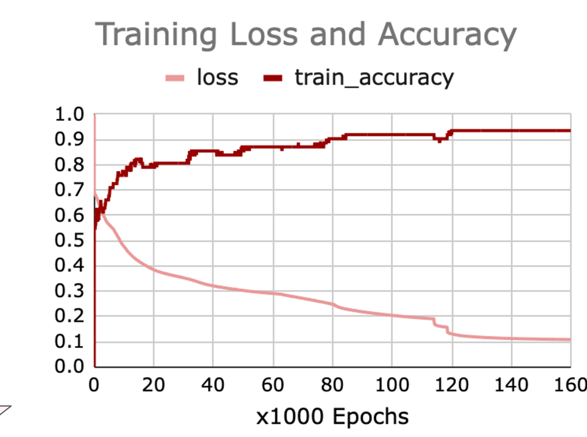

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Input layer	6 features
Hidden layer 1	8 parameters
Hidden layer 2	9 parameters
Optimizer	Adamax
Loss function	Cross Entropy Loss
Epochs	160,000
Learning Rate	0.0005

Final Results		
Metric	**Definition**	**Value**
Precision (%)	True positives / (True positives + False positives)	**90.0%**
Recall (%)	True positives / (True positives + False negatives)	**90.0%**
Accuracy (%)	(True positives + True negatives) / All samples	**87.5%**
F1 Score	(2 * precision * recall) / (precision + recall)	**0.900**
AUC	Area under curve of true positive rate vs. false positive rate	**0.870**

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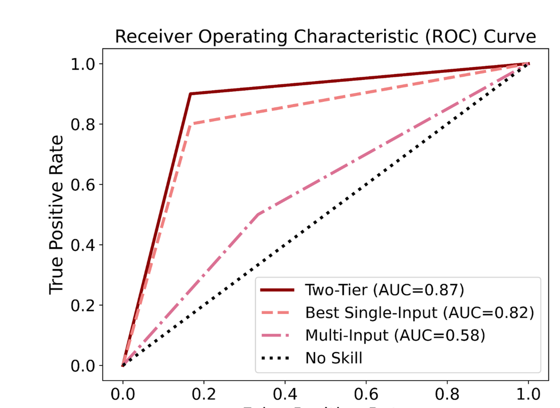

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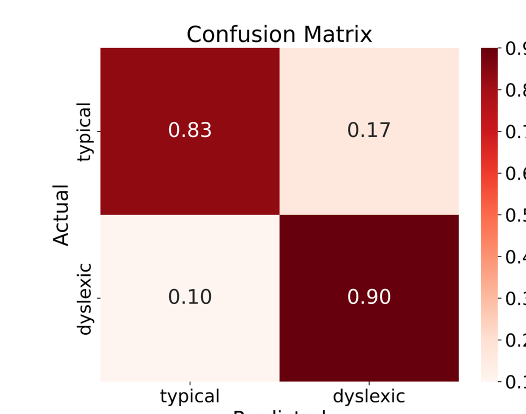

Graph created by finalist using matplotlib, 2025

MODEL CODE SNIPPETS

```python
#create model class
class Model(nn.Module):
    def __init__(self, in_features=6, h1=8, h2=9, out_features=2):
        super().__init__()
        self.fc1 = nn.Linear(in_features, h1)
        self.fc2 = nn.Linear(h1, h2)
        self.out = nn.Linear(h2, out_features)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.out(x)
        return x

interesting_columns = [x for x in list(df.columns.values) if (x in ["Part49_gm",
"Part49_wm", "Part76_gm", "Part76_wm", "Part106_gm", "Part106_wm", "out_class"])]
df = df[interesting_columns]
#convert dataframe to numpy array
X = df.drop(['out_class'], axis=1).values
y = df['out_class'].values
#train test split
torch.manual_seed(32)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```python
#instantiate model
in_feat=X_train.shape[1]
model = Model(in_features=in_feat)

#set criterion to measure loss
criterion = nn.CrossEntropyLoss()
#choose adamax optimizer (good with noisy data)
optimizer = torch.optim.Adamax(model.parameters(), lr=0.0005)

#train model
epochs = 160000
losses = []
for i in range(epochs):
    y_pred = model.forward(X_train)
    loss = criterion(y_pred, y_train)
    #print(loss)
    losses.append(loss.detach().numpy())

    #back propagation
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

#save model
torch.save(model.state_dict(), 'model_49_76_106_best.pt')
```

DISCUSSION

Selected features

Left posterior orbital gyrus, left medial orbital gyrus
- Reward and emotion
- Differences in gyri leads to difficulties associated with learning to read

Right entorhinal area
- Better memory and spatial navigation
- Makes up for left hemisphere reading networks

Pars triangularis
- Established biomarker (top 5)
- Other parts found to be better indicators

Analysis

AUC improvements: 5% over best single input model, 29% over multi-input model

Two tier model effective in improving all metrics

Comparison

6% accuracy improvement over best single input model

15% accuracy improvement over current best fMRI models

Challenges

Individual parts had too few voxels for tissue classifier

Classifying entire brain and overlapping with segmentation data worked best

Limitations

Limited publicly available training data

Limited MRI scans of young children's brains (dyslexic and normal)

CONCLUSION

01 Result
- Two tier model detects dyslexia with 87.5% accuracy in MRI scans of children's brains
- 15% better accuracy than best current fMRI models

02 Novelty
- AI eliminates manual inspection of complex brain scans, providing quick results
- More accurate than current best models
- Applicable to children before their reading years

03 Applications
- Incorporate into annual physical exam (ages 3+)
- Possibly earlier, when family history exists
- Work with doctors and educators to get early intervention

04 Future Work
- Work with dyslexia centers to acquire more training data
- Look into training different types of models (in addition to multi-layer perceptrons)

REFERENCES

1. Banfi, C., Koschutnig, K., Moll, K., Schulte-Körne, G., Fink, A., & Landerl, K. (2020). Reading-related functional activity in children with isolated spelling deficits and dyslexia. *Language, Cognition and Neuroscience*, 1–19. https://doi.org/10.1080/23273798.2020.1859569
2. Cavalli, E., Valérie Chanoine, Tan, Y., Anton, J.-L., Giordano, B. L., Pegado, F., & Ziegler, J. C. (2024). Atypical hemispheric re-organization of the reading network in high-functioning adults with dyslexia: Evidence from representational similarity analysis. *Imaging Neuroscience, 2*, 1–23. https://doi.org/10.1162/imag_a_00070
3. Eckert, M. A. (2003). Anatomical correlates of dyslexia: frontal and cerebellar findings. *Brain, 126*(2), 482–494. https://doi.org/10.1093/brain/awg026
4. Ferrer, E., Shaywitz, B. A., Holahan, J. M., Marchione, K. E., Michaels, R., & Shaywitz, S. E. (2015). Achievement Gap in Reading Is Present as Early as First Grade and Persists through Adolescence. *The Journal of Pediatrics, 167*(5), 1121-1125.e2. https://doi.org/10.1016/j.jpeds.2015.07.045
5. International Dyslexia Association. (2016). *Dyslexia basics*. Dyslexiaida.org; International Dyslexia Association. https://dyslexiaida.org/dyslexia-basics/
6. Lovett, M. W., Frijters, J. C., Wolf, M., Steinbach, K. A., Sevcik, R. A., & Morris, R. D. (2017). Early intervention for children at risk for reading disabilities: The impact of grade at intervention and individual differences on intervention outcomes. *Journal of Educational Psychology, 109*(7), 889–914. https://doi.org/10.1037/edu0000181
7. Lyon, R. (n.d.). Reading Disabilities: Why Do Some Children Have Difficulty Learning to Read? What Can Be Done About It?. WrightsLaw.
8. Raschle, N. M., Chang, M., & Gaab, N. (2011). Structural brain alterations associated with dyslexia predate reading onset. *NeuroImage, 57*(3), 742–749. https://doi.org/10.1016/j.neuroimage.2010.09.055
9. Schulte-Körne, G. (2010). The Prevention, Diagnosis, and Treatment of Dyslexia. *Deutsches Aerzteblatt Online, 107*(41). https://doi.org/10.3238/arztebl.2010.0718
10. *The Importance of Early Detection of Dyslexia | UT Permian Basin Online.* (2020, November 3). Online.utpb.edu. https://online.utpb.edu/about-us/articles/education/the-importance-of-early-detection-of-dyslexia/
11. Werth, R. (2019). What causes dyslexia? Identifying the causes and effective compensatory therapy. *Restorative Neurology and Neuroscience, 37*(6), 591–608. https://doi.org/10.3233/rnn-190939
12. Xin, et al. Characterizing Renal Structures with 3D Block Aggregate Transformers. arXiv preprint arXiv:2203.02430 (2022). https://arxiv.org/pdf/2203.02430.pdf
13. Zahia, S., Garcia-Zapirain, B., Saralegui, I., & Fernandez-Ruanova, B. (2020). Dyslexia detection using 3D convolutional neural networks and functional magnetic resonance imaging. Computer Methods and Programs in Biomedicine, 197, 105726. https://doi.org/10.1016/j.cmpb.2020.105726