Deep learning model of field imaging data provides insight on neurobiology of childhood literacy in rural Ivory Coast

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INTRODUCTION

Aim: Use Machine Learning (ML) methods to identify distinct spatial and temporal patterns of brain activity of literate, semi-literate, and non-literate groups of children and explain variation in neural activation within these groups that is not observable using traditional behavioral and neural models.

ML is a data driven method for identifying differences in patterns of neural activity not evident using traditional GLM analyses.

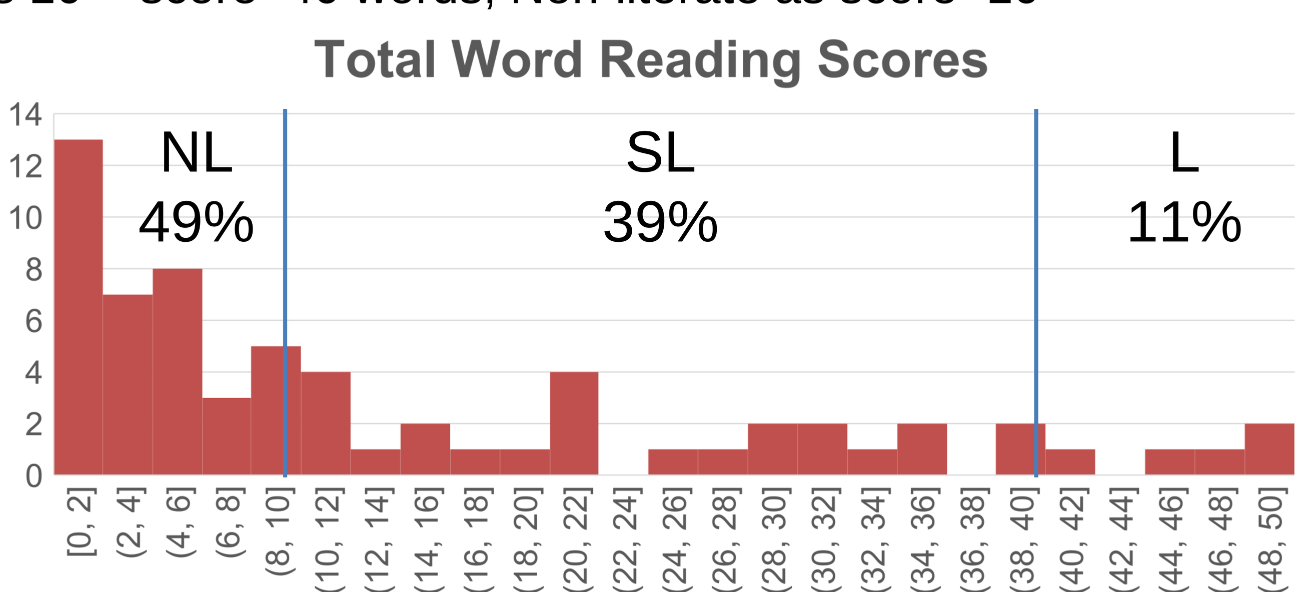
ML could identify children who are at risk for greater difficulty in learning to read and provide a method to identify neural mechanisms involved in reading. A successful deep learning model may explain why children's literacy outcomes differ based on their brain activity.

Hypothesis: We hypothesized that spatial and temporal patterns of brain activity from literate, semi-literate, and non-literate children would be distinguishable to an ML model.

METHODS

Participants: 47 children ages 7-14 years in central and southern rural Côte d'Ivoire (West Africa). Children were all emergent readers.

Literacy Assessment:
French language Early Grade Reading Assessment[1] Number of words (out of 50) children can read in 60 sec
We defined Literate children as score >=40 words, Semi literate as 10<=score<40 words, Non-literate as score<10



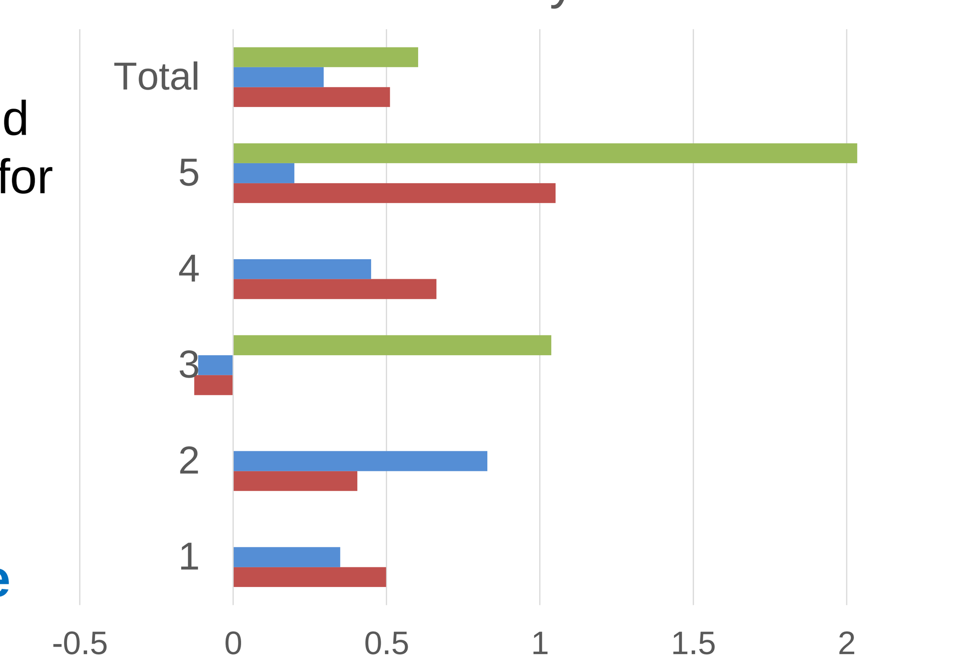
fNIRS Imaging:
LIGHTNIRS (Shimadzu, Japan) imaging systems
47 channels across the scalp to measure oxygenated and deoxygenated hemoglobin concentration changes

Task design:
Children listen to audio recordings of **words**, **pseudowords**, and **vocoded speech**, and see printed **words**, **pseudowords**, and **visual false fonts** on screen.

CLASSIFICATION RESULTS

Data Analysis:
The model was evaluated using a 5-fold cross validation method:
1. train model on 80% of the data
2. test model on 20% of the data
3. repeat this process for every 20% increment

Testing Accuracy:
Average classification accuracy was 50%
Confusion matrices were created for each fold and for the cumulative score across all folds for each classification
Cumulative d' scores for literate, non-literate, and semi-literate were .603, .511, and .295 respectively

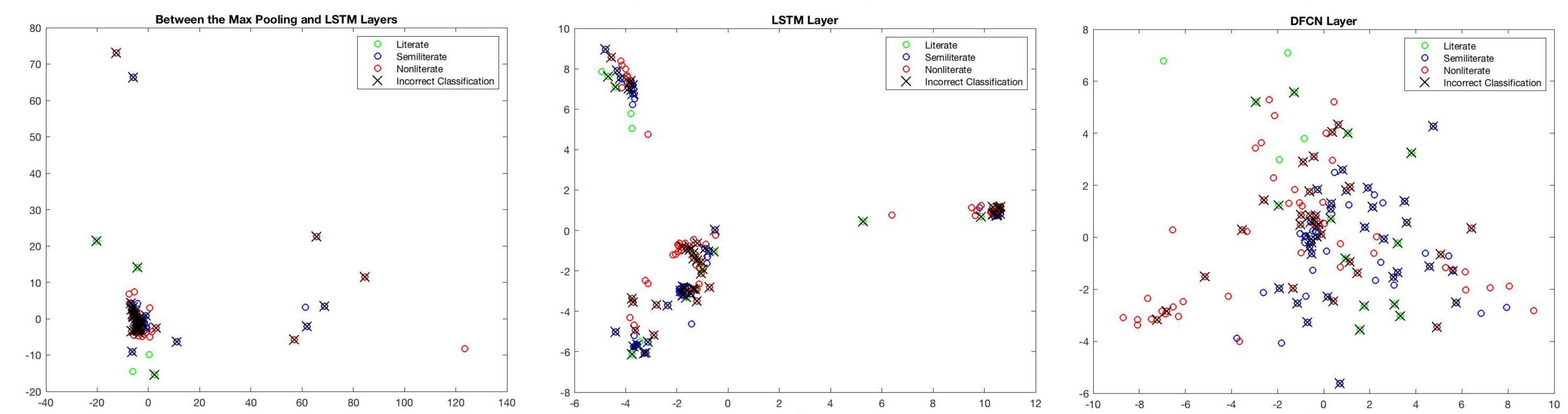


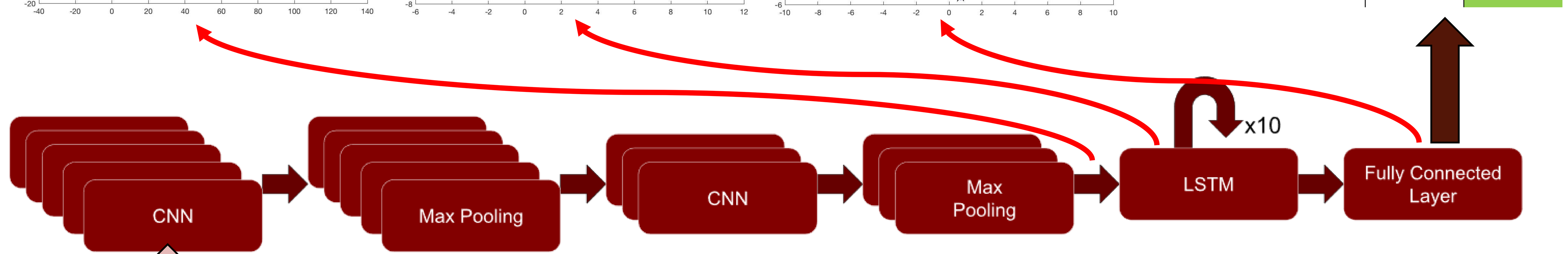
59% of Non-literate children were correctly classified
46% of Semi-literate children were correctly classified
25% of Literate children were correctly classified

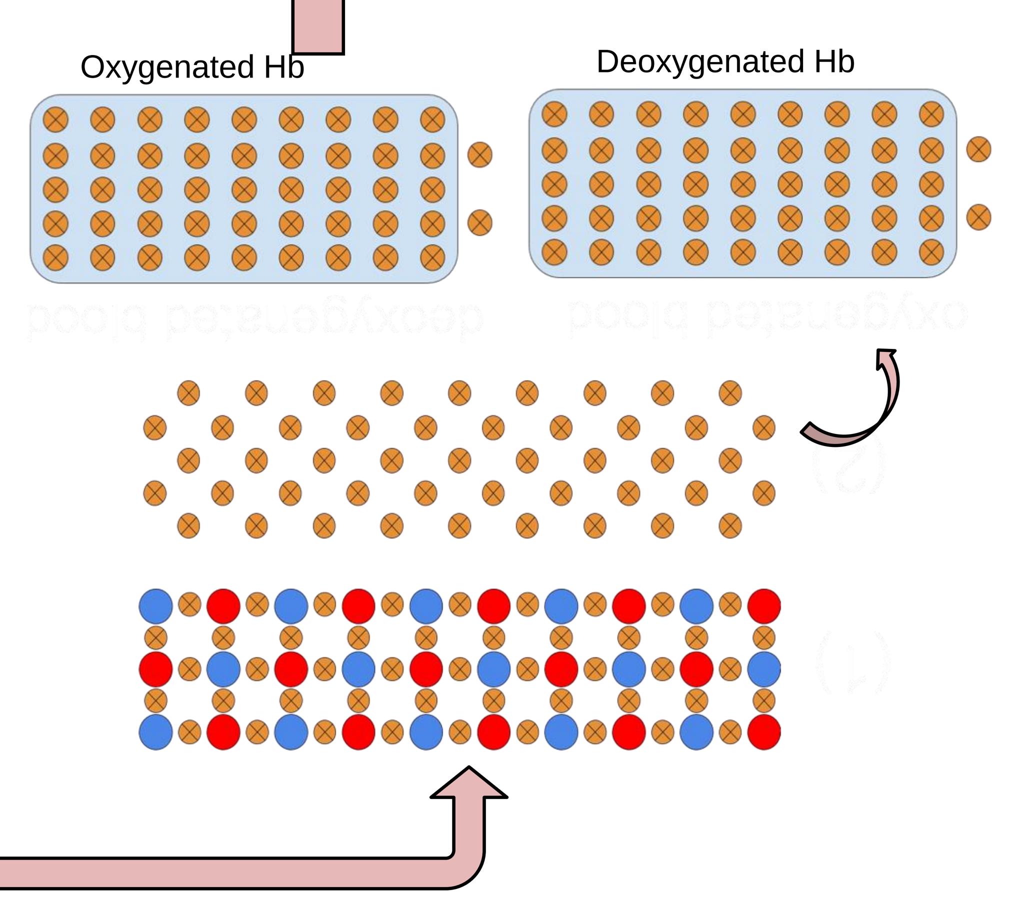
N: Non-Literate
S: Semi-Literate
L: Literate

	True N	True S	True L
Classified N	42	21	4
Classified S	22	22	8
Classified L	7	5	4

Multidimensional Scaling of Model Representations at Each Layer







NIRS probes arranged in a 3x10 layout

Two right-posterior channels are dropped to create two right aligned 5x9 matrices for Oxygenated and Deoxygenated blood.

CLASSIFICATION MODEL

The model trained to label children as Literate, Semi-Literate, or Non-literate using fNIRS brain imaging data collected during print-speech task.

Spatial Analysis (CNN) -
Convolutional neural net (CNN) convolves (or mixes) data across neighboring channels and between oxygenated and deoxygenated hemoglobin.
Spatial convolution helps to amplify local regularities among channels, and reduce small differences between participants in head shape or cap fit.

Temporal Analysis (LSTM) -
Long Short-Term Memory (LSTM) can identify patterns that occur over time
CNN passes individual time steps into the LSTM where they are combined in a time window that identifies relationships between the time steps.
This LSTM uses a window of 10 time steps (about 2.5 sec).

fNIRS Classification Model **(see diagram):**
Model design and training procedures are based on a successful fNIRS classifier for participants' emotional responses to music videos
(Bandara, Hirshfield, & Velipasalar, 2019)

DISCUSSION

Clustering in the CNN and LSTM layers suggest regularities in patterns of neural activation during the task.

The DFCN layer shows a triangular spread with clusters of correctly classified datasets in each category, at each triangle point. ***Results suggests literacy is a learnable feature present in the data.***

The model was most sensitive to classifying non-literate children. However, the literacy classification for semi-literate children were less sensitive, with less sensitive classification clustering towards the center of the triangular spread. Low sample size of literate children (n=16) limited interpretation of model classification.

The results reveal more variation in patterns of neural activation for reading, which may suggest variation in learning mechanisms that support literacy in this low-literacy sample (e.g. variation in age)

FUTURE DIRECTIONS

Optimization of the network can improve by understanding spatial features, time windows, and stimulus types that are relevant to this dataset and this task

A larger dataset, especially for Literate condition, is crucial to improve training

Search parameter space to optimize the classification accuracy

Excluding specific channels time windows for clues about relevant signals

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