

EEG Based

AI based Differential diagnosis of dementia
etiologies on multimodal data.

- There is overlap of etiologies, crucial for formulating early personalised management strategies
 - multiple types of data:
 - ↳ medical history
 - ↳ medication use
 - ↳ funct. eval.
 - ↳ Neuroimaging
 - Microaveraged AUROC of 0.94
 - ↳ normal cognition
 - ↳ mild cognitive impairment
 - ↳ Dementia
- 51,269 participants
9 geo datasets

Better than 26.5% over neurologist
of 100 subset cases.

- Not only accurate aligned with biomarker evidence
- Biomarker → measures (like protein in blood)
- The A₄ is allele to correlate (Near 1) to different protein patterns (D)

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- NC → Normal cognition
 - MCI → Mild cognitive impairment
 - DE → Dementia
 - AD → Alzheimer Disease
 - VD → Vascular Dementia
 - ODE → Other Dementia

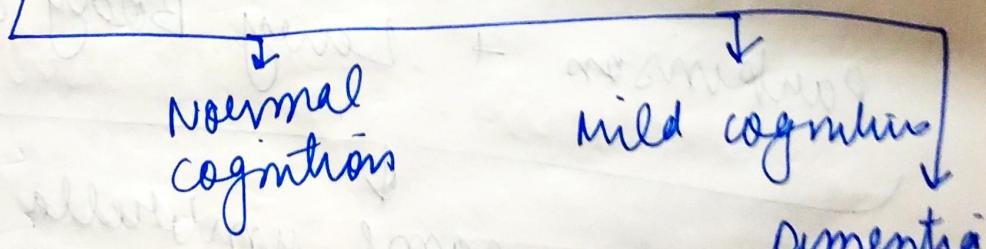
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- So patient with Alzheimer may be candidate for anti amyloid treatment
 - But if the patient has other types of dementia like Vascular Dementia, it can complicate amyloid-related imaging
 - Can create amyloid-related imaging anomalies.

- Lack of gold standard testing, diminishing pool of dementia clinics
- regulatory labs have allowed us to move some biomarker test from labs to clinics
- accessibility is still constrained.
- prolonged waiting time
- lack of appropriate due to lack of formal training.

PROBLEMS

Previous works

- ↳ only uses neuroimaging data to distinguish

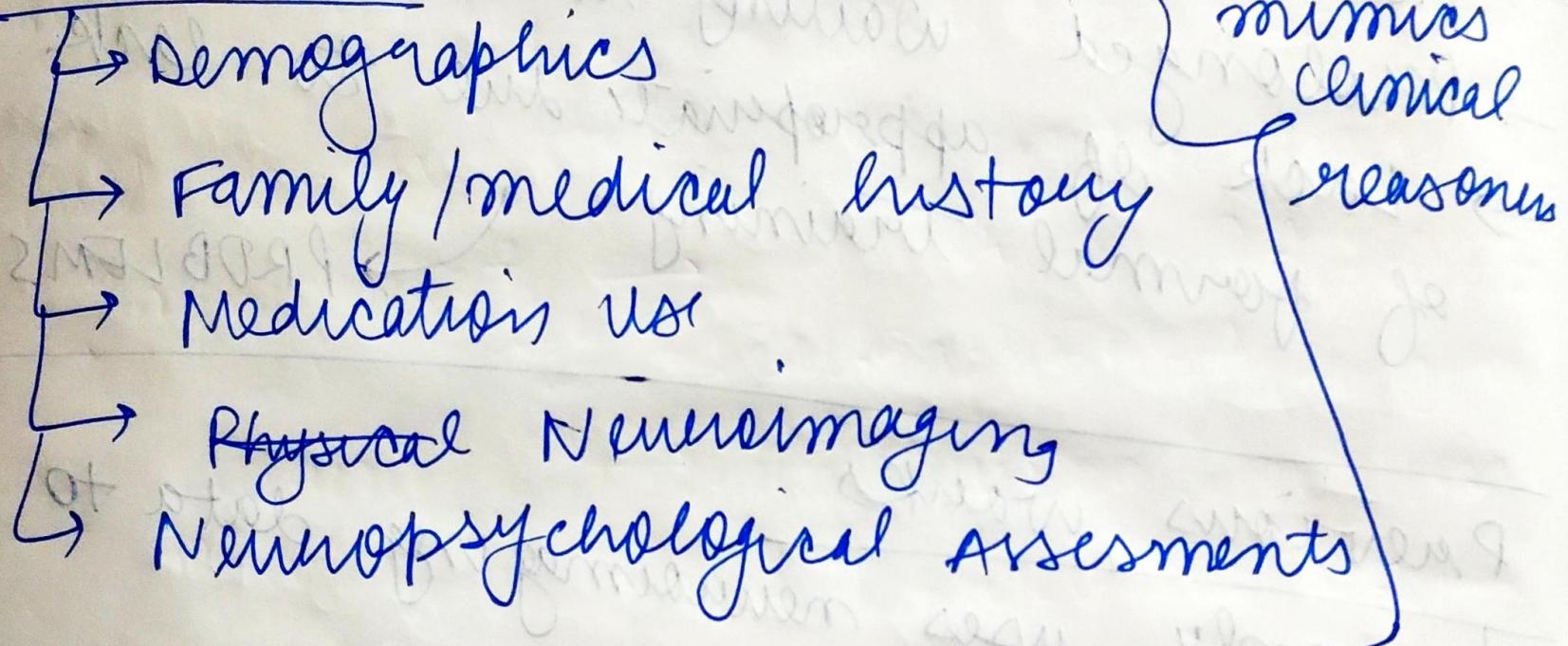


- Trained contrastive learning

AD → (Alzheimer Disease) ← with other dementia types.

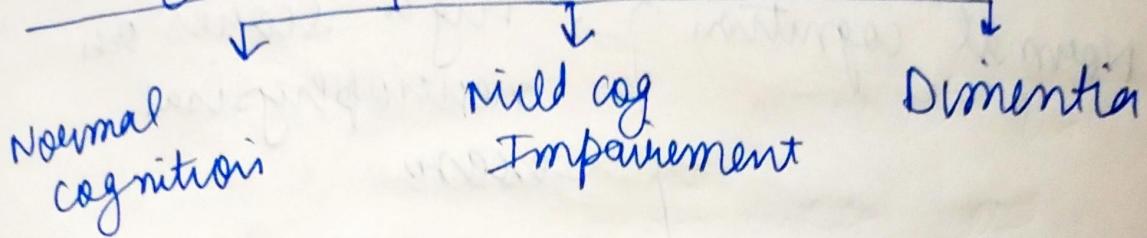
- Just as Alzheimer can have limited applications as co-occurrences with other etiologies
- Image data alone is insufficient to understand ones medical approach.

Multimodal



Parkinson + Lewy Body dementia

3 way classification model



- Performance using ROC + Precision, Recall
(receiver operating characteristic)
- unused data from National
Alzheimer Coordinating center.

results

$$\textcircled{A} \text{ AUROC} = 0.94$$

$$\text{AVPR} = 0.90$$

etc - - -

Baseline → Cat Boost. Model

④ Shapley Analysis

- ↳ which feature most influenced
model's diagnostic decision

what did Snappy Analysis tell

Normal cognition → high scores on neurophysiological exam

High score on montreal cogn. assess

Better perf in memory task.

Mild Cognitive Impairment

→ similar memory related features

→ functional impairment and T-weighted MRI

T, W → scans that show scans of brain atrophy

Dementia

→ functional impairment has most influence

→ MMSE assignment low scores,

missing Data Handling

- remove portions of data to mimic that.
- Types of data simulated
 - MRIs
 - Unified Parkinson Disease
 - G Depression Scale
 - NP test

model told β strong correlation
of Pre Alzheimer Disease & mild cog I

- Differentiates b/w AD & Non AD
even at MCI stage underlines
potential in clinical setting

in respect to CDR (Clinical Dementia Rating).

Compare Probability of Dementia

to CDR score

$P(D)$ \rightarrow CDR

→ CDR was not used during input of model training.

- Helps to independent the predictions
- Avoids circular logic
- Tests generalisability

~~NAE~~

→ For ADNI dataset

- RDE) increased with high CDR scores
- statistically significant differences along spectrum of cognitive impairment.

→ Good tool for general diagnosis even when not trained for CDR score.

Limitation → Difficulty in distinguishing early stage of cognitive decline in FHS dataset

→ Due to limited feature set of FHS.

Evaluation & Results

- 10 different dementia etiologies
- AUROC = 0.96 AUPR = 0.7
- Macro Avg AUROC = 0.94 , AUPR: 0.73
- High micro AUROC + weighted avg score → good performance across all dementia types
- Lower Macro AUPR → varying performance across different diagnostics

AUROC for co occurring dementia
AUROC ranges from

$$0.63 \rightarrow 0.97$$

- This defines that model performance varies from different combination of dementia.
- AUROC = 0.5 → random guess

LBD + PSY

Lewy Body Dsm + Psychiatric Disease

were most accurate

Thus the model is good at predicting co-occurrence of conditions.

Limitation

- Not tested for all ethnic backgrounds
- mostly white population
- Asian countries don't specifically give you a lot of data sample to look & make assumptions about
- Performance varies across different data cohorts NACC, ADNI
- Model may bias towards Alzheimer disease

- Annotation for model training is uncertain as it
- Conditions like ~~SEF~~ SEF & TBI were challenging to assess with limited feature sets
- Dementia in itself can be mild, severe, moderate but it isn't covered.

Methods & Models

Data → 341 non imaging features across various aspects of participant health & cognition

- Categorical inputs were encompassed with a lookup table to ensure in data space.

Images \rightarrow Embeddings.

1. MODEL.

Swin ViT

↓
Transformer Base

↓
Four MRI scans (T_{2w} , T_{2w} , sw_1)

↓
Broken in 2 parts

(a) Swin transformer encoder
: Processes 3D patches of input
image.

(b) CNN decoder : Reconstructs
the image from encoded
representation.

in

x is the dim

ENCODER

- 3D input $\rightarrow H \times W \times D$.
- Encoder segments x into 3D tokens with dimension $H'/H \times W'/W \times D'/D$

- Projected into C -dimensional space ($C = 48$) using embedding layer
- Patch size = $2 \times 2 \times 2$
- Feature dim = $2 \times 2 \times 2 \times 1$
- skip connections to combine encoder outputs with NN decoder.

Model trained on 3D volumes of chest abdomen, neck / head.

Decoder

- connected to the encoder through multi resolution skip connection
- V shape network
- combines encoder output at diff resolution
- generates & re-constructs of initial input volume.

Pre Train

- Pre trained using self supervised approach

MRI Pre - processing

- resample to standard pixel dimension
- foreground cropping
- spatial crop-size $\rightarrow 128 \times 128 \times 128$

model extracts encoder output size

$$\hookrightarrow 768 \times 4 \times 4 \times 4$$

Embedding Generation

- Extracted feature go downsampling
- Learnable embedding module with four convolutional blocks
- 1 vector output of 256 each MRI scans