

The potential for Artificial Intelligence in the diagnosis of Alzheimer's Disease

A SYSTEMATIC LITERATURE REVIEW

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AGENDA

- Context and Background
- Medical Imaging
- Data Preprocessing
- Possible Approaches
- Implications
- Future Directions

CONTEXT AND BACKGROUND

ALZHEIMER'S DISEASE

The most common form of irreversible dementia

- Mild Cognitive Impairment generally represents early-stage AD
- **A validated treatment still does not exist**
- Diagnostic methods
 - i. Clinical symptoms and cognitive function examination scales*
 - ii. Biomarker-based methods (e.g. cerebrospinal fluid)*
 - iii. Neuroimaging-based methods*

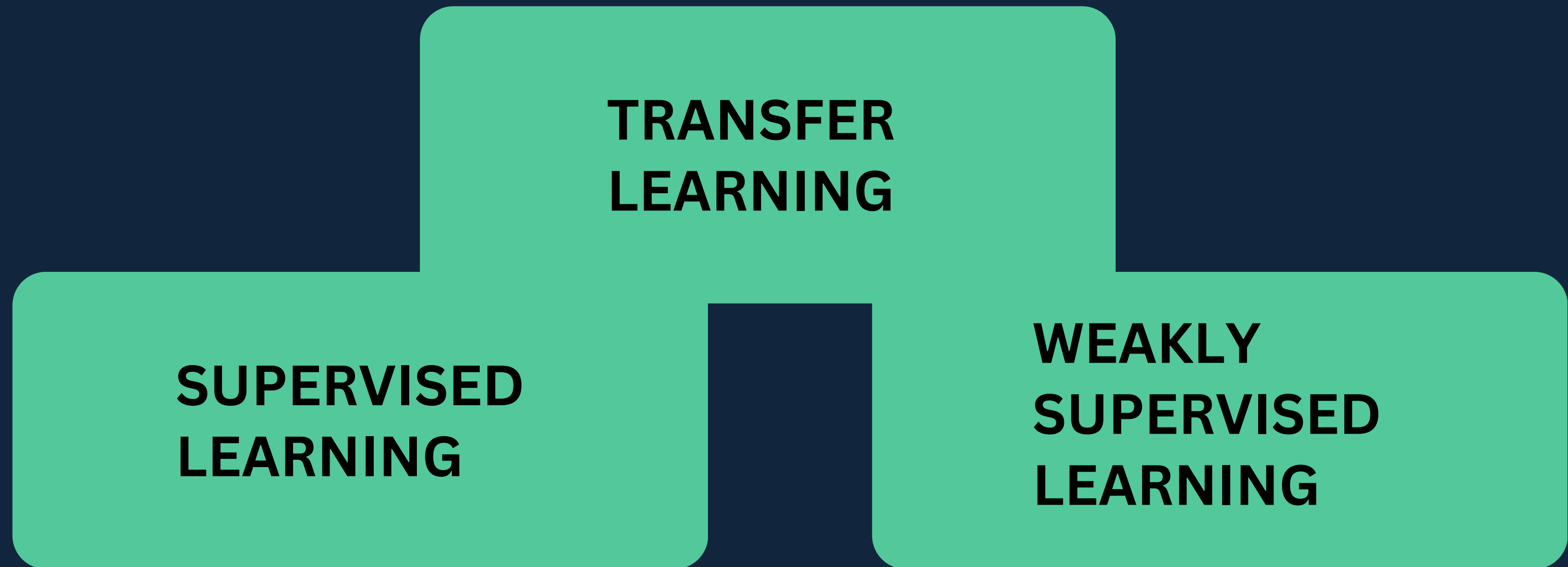
MEDICAL IMAGING

- Misalignment between human instinct and standard measurements
- Importance of computer-aided systems for accurate diagnosis
- **Magnetic Resonance Imaging (MRI)** as the preferred neuroimaging technique
- The increased lifespan adds further complexity
- Shift to personalised medicine --> role of *Artificial Intelligence*

DATA PREPROCESSING

- Importance of preprocessing
- Difficulty in image reconstruction
- Various feature extraction methods
 - i. Voxel
 - ii. Slice
 - iii. Region Of Interest (ROI)
 - iv. Patch
- Growing relevance of **ML (DL)**, alongside its **challenges**

POSSIBLE APPROACHES



SUPERVISED LEARNING

- Supervised learning is a branch of ML that utilises labeled datasets to train algorithms in predicting outcomes and identifying patterns
- Therefore, supervised learning relies on labeled training data to establish relationships between inputs and outputs
- SL algorithms analyse dataset and labels for then inferring on new data

CHALLENGES

- Insufficient number of annotated data
- Cost and time constraints
- Dependence on the quality (e.g. granularity) of annotations

WEAKLY SUPERVISED LEARNING

Characterised by using a combination of a small amount of human-labeled data (typical of Supervised Learning), followed by a large amount of unlabeled data (typical of Unsupervised Learning)

3 MAIN TYPES

**Incomplete
Supervision**

**Inexact
Supervision**

**Inaccurate
Supervision**

WEAKLY SUPERVISED LEARNING

Incomplete Supervision

Only a small portion of training data is labeled



Active learning

Human intervention (“oracle”) for labelling significant data used for ground-truth



Semi-supervised learning

In this technique test data are not known and the unlabeled data are not necessarily test data

A subset of Semi-supervised learning is Transductive Learning, where the unlabeled data is instead precisely test data

WEAKLY SUPERVISED LEARNING

Inexact supervision

Where some supervision
information is provided,
but it lacks precision



For example with the presence
of coarse-grained supervision

WEAKLY SUPERVISED LEARNING

**Inaccurate
supervision**

The given labels are not always ground-truth e.g. due to the human annotator fatigue



Example:
crowdsourcing

It should be highlighted that WSL in general, can help protect privacy by examining data that lacks full annotations

WEAKLY SUPERVISED LEARNING – ADGNET (LIANG AND GU)

- Backbone network and the task networks
- Attention mechanism adjusts the weights of the channels in the feature maps
- Five convolution stages
- Two sub-networks for image reconstruction and image classification in parallel

WEAKLY SUPERVISED LEARNING – WSDL (ZHANG ET AL.)

- Incomplete supervision
- Attention Mechanism using the relationship between channels
- Consistent regularization of unlabeled samples
- First regularization term counters the model's tendency to favor predictions for more categories
- Second regularization term avoids overfitting
- Modules are mutually reinforcing

WEAKLY SUPERVISED LEARNING – WADP (CHEN ET AL.)

- Predict cognitive scores using MRI baseline data and weakly labeled data
- Image embedding network extracts the Class Activation Mappings (CAMs)
- Attention consistency captures the correlations among time-points
- Label embedding network to make full use of all available samples
- Relation alignment module to make the embedding space discriminative

TRANSFER LEARNING

ML technique in which knowledge acquired by a model in a particular context or task, is transferred and applied to improve the performance of the model in a related or similar context or task

-➤ Enables the utilisation of expertise gained from solving one problem to address a similar one
-➤ It is like a **bridge** that makes it possible the coexistence of both Supervised and Unsupervised Learning

2 STEPS

- Unsupervised pre-training
- Supervised fine-tuning

DEEP BELIEF NETWORK (FATURRAHMAN ET AL.)

Example of the application of Transfer Learning in AD detection

3 STEPS

- **Pre-processing and Feature extraction** of structural MRI data employing a voxel-based morphometric (VBM) approach to clean and reorganise data for following analysis
- **Unsupervised Pre-training** phase (hierarchical representation of data) by mean of DBN
- **Supervised fine-tuning** phase (use of labelled data to increase overall performance of the model optimising its weights)



Once the model has been fully trained, it is tasked with identifying patients with AD and healthy ones

ETHICAL IMPLICATIONS

Lack of trustworthiness of AI-based Clinical Decision Support Systems (CDSSs)

- data-related issues
- poor integration into the clinical workflow
- model opacity

Trustworthy Artificial Intelligence (TAI)

Chain of trust

ETHICAL IMPLICATIONS

TAI REQUIREMENTS

~~Societal and environmental
well-being~~

Human agency and oversight

Technical robustness and safety

Diversity, non-discrimination,
and fairness

Accountability

Transparency

Privacy and data governance

- Challenging operationalisation of TAI requirements
- Simultaneous consideration of TAI dimensions
- Higher community trust

LEGAL IMPLICATIONS

EU placed important attention on this topic recently, to ensure that ethical or legal risks do not compromise benefits

EU Regulatory framework

- Data Governance Act
(increase *trust in data sharing*)
- Artificial Intelligence Act
(hidden/visible *discrimination by algorithms*)
- European Declaration on Digital Rights and Principles for the Digital decade
(*Transparency*)

This underscores the importance of placing humans at the heart of digital transformation

POTENTIAL SCENARIO

The advantages of both Supervised and Unsupervised models can be exploited thanks to Transfer Learning, effectively addressing the challenges associated with each

- Companies developing ML Models pre-train models, subsequently offering pre-trained models to healthcare facilities
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- Healthcare facilities undertake fine-tuning of the models, reducing the need of new skills for medical professionals

*Of course this will lead to a new set of skills / professionals
needed by the healthcare system*

PRACTICAL IMPLICATIONS

- A skill shift is required
- Forward-looking responsibility

—————→ Enrichment of **Entrustable Professional Activities** (Sand et al.)

Reporting and informing about sensitivity rates and experimental performance

Understanding reasonable output

Understanding input data

Awareness of impact of utilizing AI on one's own skills and capacities

Awareness of task specificity of the medical AI

Assessing, monitoring, and reporting of outputs over time

FUTURE DIRECTIONS

Noninvasive biomarkers

Explainable AI (XAI)

Patient-doctor dynamics

Thank you