Adaptive Per-Patient Behavioural Monitoring for Early Detection of Cognitive Decline in Dementia

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► Motivation

Dementia affects ~55M people worldwide (≈139M by 2050) and progresses in a highly individual way. Yet most AI monitors use population-level thresholds fixed at deployment [1], [2], missing early decline that stays inside the normal range, and raising false alarms that erode caregiver trust.

Static system asks: *is this patient abnormal vs. the population?*

Adaptive system asks: *has this patient changed vs. themselves?*

► Objectives

- Leakage-free, patient-level baseline, benchmarked vs. XGBoost and an FT-Transformer.
- Unsupervised Isolation Forest severity signal, validated against clinical ground truth.
- Per-patient adaptive thresholding that catches early decline static rules miss.
- Candid evaluation and generalisation to other progressive conditions.

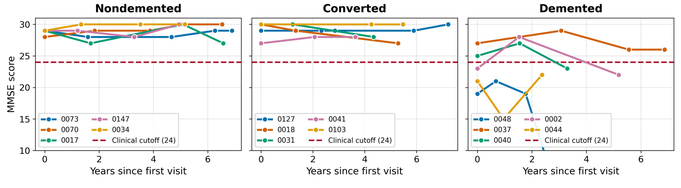


Fig. 1. *Individual MMSE trajectories by group (dashed = clinical cut-off 24). The diversity of shapes justifies per-subject modelling.*

► Dataset — OASIS-2

150	373	14
subjects	visits	converted

150 subjects aged 60–98 · 2–5 visits ≥ 1 yr apart. 72 Nondemented · 64 Demented · 14 Converted. The **Converted** subgroup is central and exactly where fixed thresholds fail. Public and fully anonymised.

► Methods

- Features: Δ(MMSE, CDR, nWBV), MMSE-decline slope, visit-regularity index, age-adjusted brain-volume ratio, no future→past leakage.
- Patient-level split (GroupShuffleSplit, 75/25); Converted group withheld as an independent early-detection test.
- Random Forest vs. XGBoost vs. FT-Transformer on identical features, split and seed.
- Isolation Forest: a label-free severity score.
- Adaptive per-patient threshold, baseline from initial visits; alert on deviation in units of each patient's own variability.

► Results — Classification

Model	Acc	Prec	Rec	F1	AUC
Random Forest	**0.854**	0.810	0.895	0.850	**0.935**
XGBoost	0.817	0.767	0.868	0.815	0.908
FT-Transformer	0.817	0.756	0.895	0.819	0.898

Held-out 82 visits, 34 unseen patients. The leakage-free split corrects an optimistic 89.3% to an honest 85.4%.

► Headline — Static vs. Adaptive

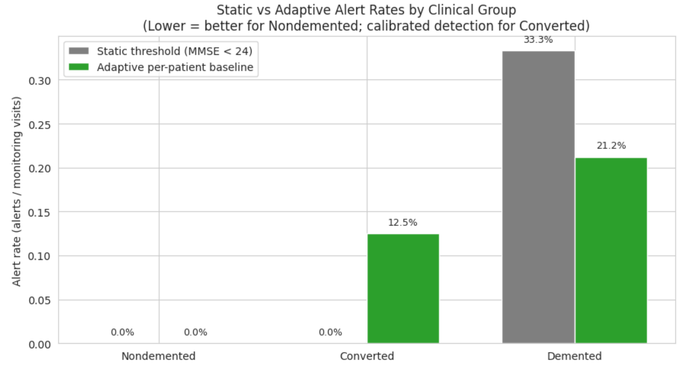


Fig. 2. *Alert rates by clinical group across the two strategies.*

Converted group: static 0% → adaptive 12.5%
0% false alarms on stable patients

► Conclusion

Individually calibrated, change-sensitive monitoring catches early deterioration static thresholds miss without the false alarms that drive abandonment. Disease-agnostic: Parkinson's, CHF, COPD, frailty.

Future Recommendations: caregiver-text NLP · wearable validation · larger cohorts · usability.

► References

[1] R. Mohan, P. Borugadda, N. R. Lavuri, and S. Venugopal, "An IoT-assisted Alzheimer's disease patient monitoring system using adaptive deep learning models," *EURASIP J. Adv. Signal Process.*, vol. 2026, no. 1, p. 26, 2026.

[2] A. Ali *et al.*, "An innovative IoT and edge intelligence framework for monitoring elderly people using anomaly detection," *Sensors*, vol. 25, no. 6, p. 1735, 2025.