

Course: Multi-modal Data Science and Engineering (MDSE)

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Multimodal Data Science and Engineering (MDSE)

Course by research papers.

Every topic will include:

1. Topic/task/problem specification
2. Previously published methods for solving the problem
3. Description of the new method and the publication where it is published
4. **Software implementation**, experimental results and discoveries
5. Applications
6. Future work to be done for this problem and questions for individual work

[Additional materials: - relevant papers;](#)

[- https://www.knowledgeengineering.ai/china](https://www.knowledgeengineering.ai/china)

[ZOOM link for all lectures: https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRcN3o4K0FaZ0lqQmN1UUgydz09](https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRcN3o4K0FaZ0lqQmN1UUgydz09)



What is MDSE and why we need it?

Definition: MDSE is a new discipline in science and engineering that develops new methods and their engineering implementations for integrated processing of multiple modalities (e.g. different types) of data into one system, including *different time and space scales*, for a better performance when compared with systems that deal with single modalities.

Advantages:

- MDSE offers a *wholistic approach* to a better problem solving, considering multiple related factors.
- MDSE can extract novel associations between different modalities of data for new knowledge discovery.
- MDSE can offer a better prediction of future events.

Examples:

- Integrating multiple medical factors in health predictive modelling
- Integrating multiple sensory information for environment prediction
- Integrating audio and visual information
- Integrating multiple factors for financial and economic prediction



Full List of Topics/Lectures:

1. Introduction to the course: What is MDSE and why we need it?

2. Methods for MDSE:

- [paper: S.Budhraj, B.Singh, S.Tan, M.Dobrojuh, Z.Doborjuh, W.Goh, E.Lai and N.Kasabov, Mosaic LSM: A Liquid State Machine Approach for Multimodal Longitudinal Data Analysis, Proc. International Joint Conference on Neural Networks \(IJCNN\), Gold Coast, Australia, 2023, pp. 1-8, doi: <https://doi.org/10.1109/IJCNN54540.2023.10191256>; <https://ieeexplore.ieee.org/document/10191256>. IEEE, 2023, ISBN:978-166548867-9](#)
- [Software NeuGems: <https://kedri.auf.ac.nz/news-and-events/introducing-neurogems>](#)

3. MDSE for integration of static and temporal multimodal biomedical data

- *Paper 1: Li, Jiawei; Liu, Jinyuan; Zhou, Shihua; Zhang, Qiang; Kasabov, Nikola, "GeSeNet: A General Semantic-guided Network with Couple Mask Ensemble for Medical Image Fusion", IEEE Transactions on Neural Networks and Learning Systems, DOI: <https://doi.org/10.1109/TNNLS.2023.3293274>, 21 July 2023.*
- *Paper 2: M. Doborjuh, N. Kasabov, Z. Doborjuh, R. Enayatollahi, E. Tu, A. H. Gandomi, Personalised modelling with spiking neural networks integrating temporal and static information, Neural Networks, 119 (2019), 162-177.*
- *Paper 3: Sengupta, N., McNabb, C. B., Kasabov, N., & Russell, B. R. (2018). Integrating Space, Time, and Orientation in Spiking Neural Networks: A Case Study on Multimodal Brain Data Modelling. IEEE Transactions on Neural Networks and Learning Systems, 29(11). doi:10.1109/TNNLS.2018.2796023*

4. MDSE for predictive modelling of multisensory streaming data

- *Paper 1: Maciag, Pi; Bembenik, R; Piekarczywicz A, Del Ser L, Javier, L, Lobo, J; N Kasabov;, Effective Air Pollution Prediction by Combining Time Series Decomposition with Stacking and Bagging Ensembles of Evolving Spiking Neural Networks, Environmental Modelling and Software, vol.170, on line: 16.10.2023, Dec 2023, 105851, <https://doi.org/10.1016/j.envsoft.2023.105851>; <https://www.sciencedirect.com/science/article/pii/S1364815223002372>*
- *Paper 2: H Liu, G Lu, Y Wang, N Kasabov, Evolving spiking neural network model for PM2.5 hourly concentration prediction based on seasonal differences: A case study on data from Beijing and Shanghai, Aerosol and Air Quality Research, vol.21, Issue 2, Feb. 2021, 200247, <https://doi.org/10.4209/aaqr.2020.05.0247>*
- *Paper 3: Laña I, Lobo JL, Capecci E, Del Ser J, Kasabov N, Adaptive long-term traffic state estimation with evolving spiking neural networks, Transportation Research Part C: Emerging Technologies 101:126-144 2019, <https://doi.org/10.1016/j.trc.2019.02.011>*

5. MDSE for integrated audio-visual information processing

- *Paper 1: N. Kasabov et al, AVIS: a connectionist-based framework for integrated auditory and visual information processing. Inf. Sci. 133, 137– 148 (2000)*
- *Paper2: N Kasabov, B Bhattacharya, D Patel, N Aggarwal, T Bankar, I AbouHassan, Cognitive Audio-Visual Associative Memories using Brain-inspired Spiking Neural Networks with Case Studies on Moving Object Recognition (IEEE Trans. Cognitive and Devel. Systems, 2023).*

6. MDSE for integrating times series and text data in finance and economics (Ms Iman AbouHassan)

- *Paper: I AbouHassan, N Kasabov, V Jagtap, P Kulkarni, Spiking neural networks for predictive and explainable modelling of multimodal streaming data on the Case Study of Financial Time Series Data and on-line news, SREP, Springer-Nature, Sci Rep 13, 18367 (2023). <https://doi.org/10.1038/s41598-023-42605-0>*

7. MDSE for integration of brain data and face image data for emotion recognition

- *Paper: C Tan; G Ceballos; N Kasabov; N Subramaniam, FusionSense: Emotion Classification using Feature Fusion of Multimodal Data and Deep learning in a Brain-inspired Spiking Neural Network, Sensors (ISSN 1424-8220), MDPI Publisher, September 2020*

8. Revision of the course



Lecture 2: Methods for MDSE

paper: S.Budhraja, B.Singh, S.Tan, M.Dobrojuh, Z.Doborjeh, W.Goh, E.Lai and N.Kasabov, *Mosaic LSM: A Liquid State Machine Approach for Multimodal Longitudinal Data Analysis*, Proc. International Joint Conference on Neural Networks (IJCNN), Gold Coast, Australia, 2023, pp. 1-8, doi: <https://doi.org/10.1109/IJCNN54540.2023.10191256>; <https://ieeexplore.ieee.org/document/10191256>. IEEE, 2023, ISBN:978-166548867-9

Software NeuGems: <https://kedri.aut.ac.nz/news-and-events/introducing-neurogems>

- **Early integration of different modalities:**

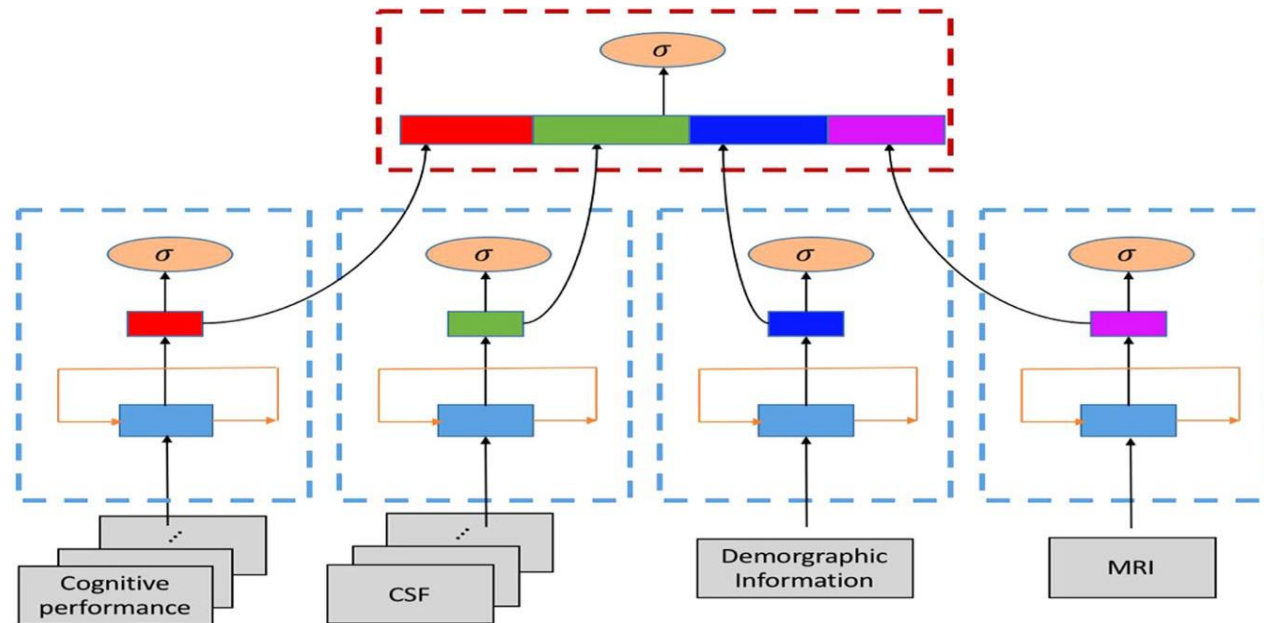
Forming single vectors of all modality variables and then creating a model based on these vectors

- **Late integration:**

Each modality is used to create a separate model and then the models are integrated

- **Mixed integration:** Some of the modality variables are integrated early and some late, with a final late integration at the output

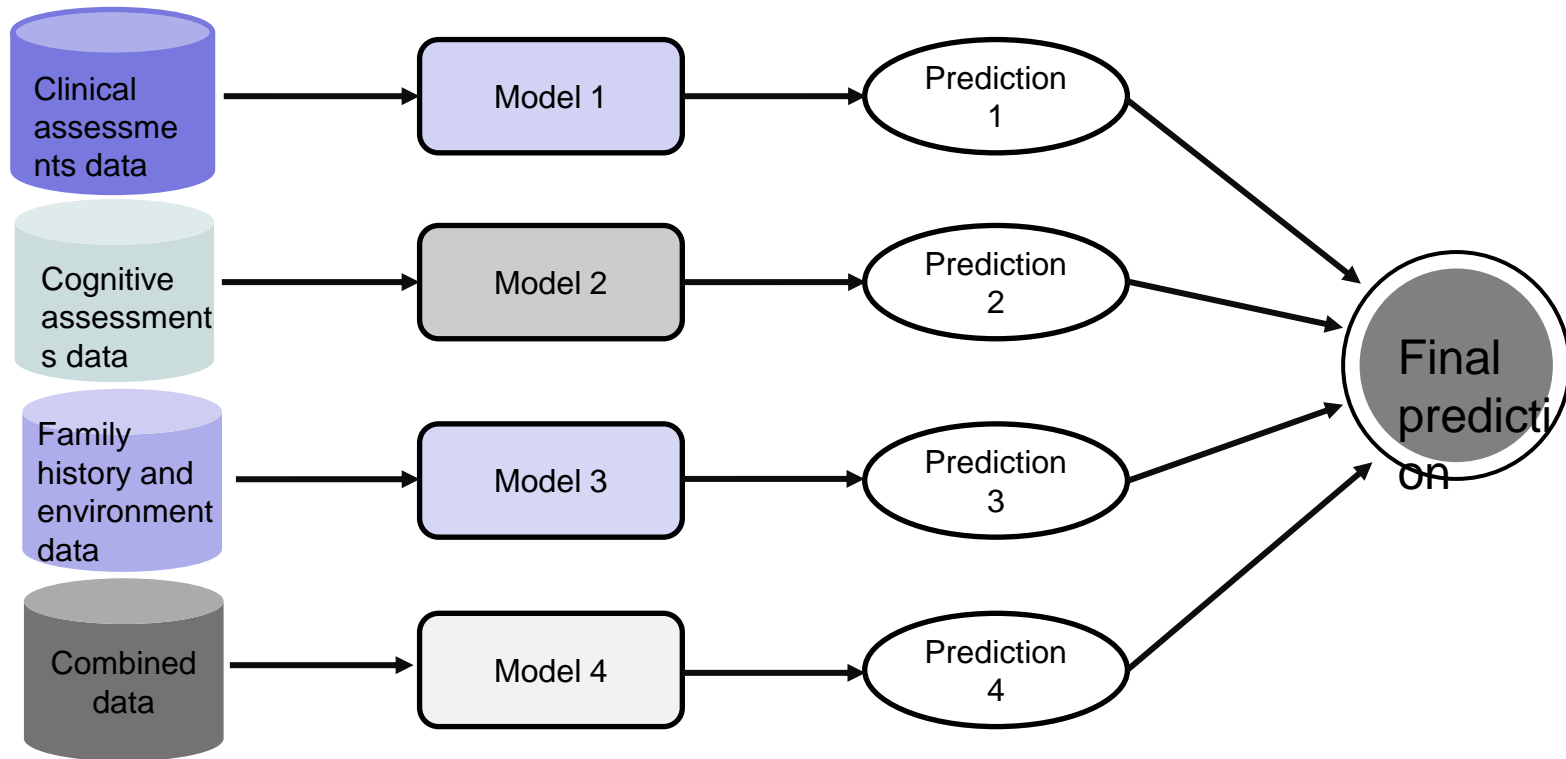
Example of early integration of multiple modalities



Paper: Garam Lee¹, Kwangsik Nho, Byungkon Kang, Kyung-Ah Sohn, Dokyoon Kim, Predicting Alzheimer's disease progression using multi-modal deep learning approach, *Scientific Reports* | (2019) 9:1952 | <https://doi.org/10.1038/s41598-018-37769-z>

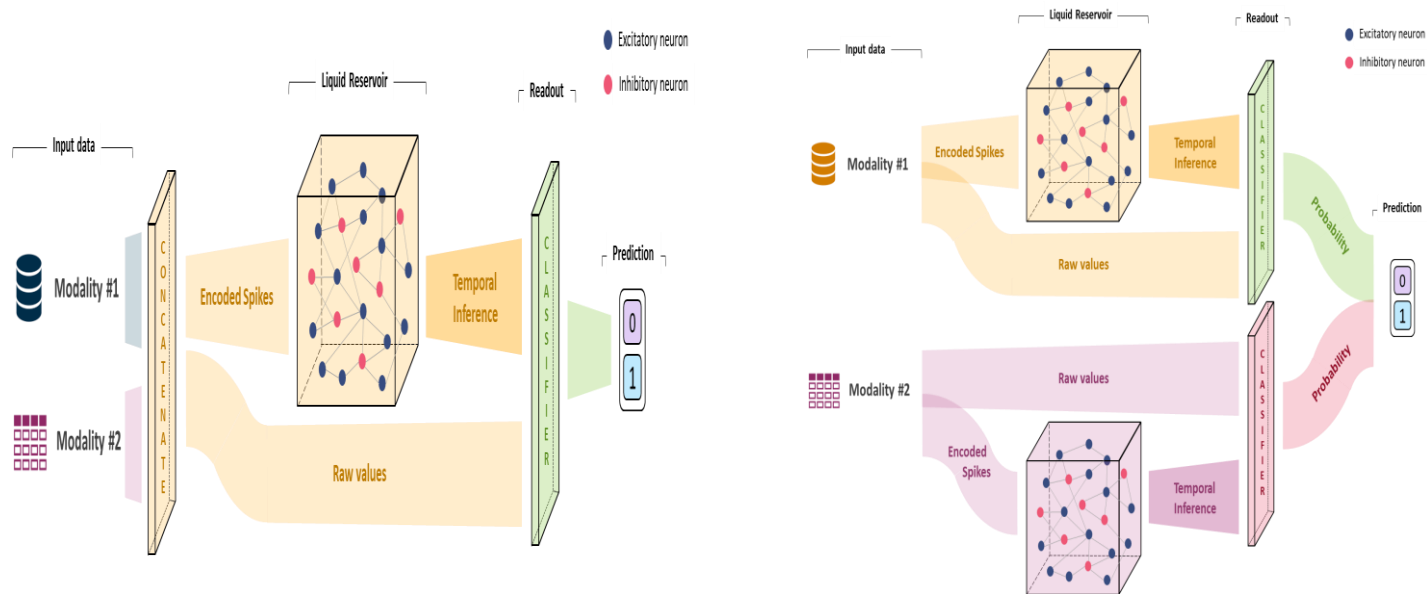
Multiple modules accept each modality of the dataset. At the first training step (blue dashed rectangle), each component takes both time series or non-time series data to produce fixed-size feature vectors. And then the vectors are concatenated to form an input for the final prediction in the second training step (red dashed rectangle)

Example of late integration multi-modal system

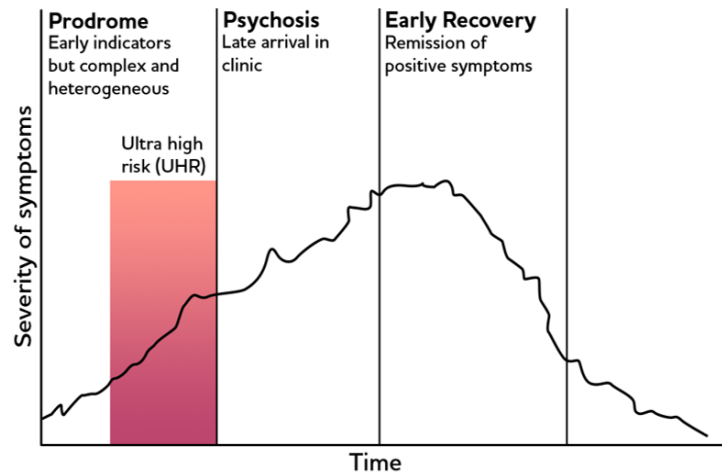


Examples of mixed integration multimodal systems

The paper for this lecture: S.Budhraja, B.Singh, S.Tan, M.Dobroreh, Z.Doborjeh, W.Goh, E.Lai and N.Kasabov, Mosaic LSM: A Liquid State Machine Approach for Multimodal Longitudinal Data Analysis, *International Joint Conference on Neural Networks (IJCNN)*, Gold Coast, Australia, 2023, pp. 1-8, doi: 10.1109/IJCNN54540.2023.10191256; <https://ieeexplore.ieee.org/document/10191256>.



Case study data



LYRIKS dataset: A rich multimodal dataset comprising clinical, cognitive, and genetic information on Ultra-High Risk (UHR) mental states collected over two years.

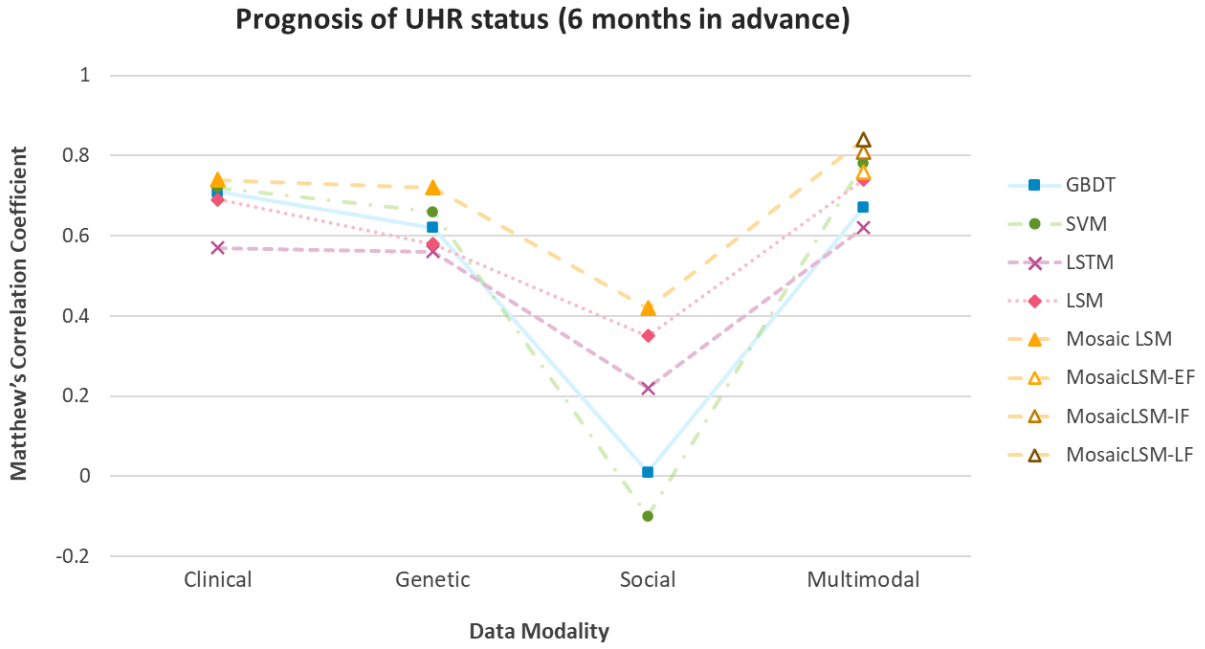
Task: Primary objective was to predict UHR psychosis status 6 months in advance based on 18 months of temporal data.

Participants: Out of 66 comprehensive participants, 40 classified as no-risk, 26 as at-risk.

Imputation: Missing values addressed via temporal interpolation to maintain longitudinal integrity.

Data Encoding: The data was encoded into spike trains using step-forward method, expanding 4 timesteps to 52 timesteps to stimulate activity in the LSM reservoir.

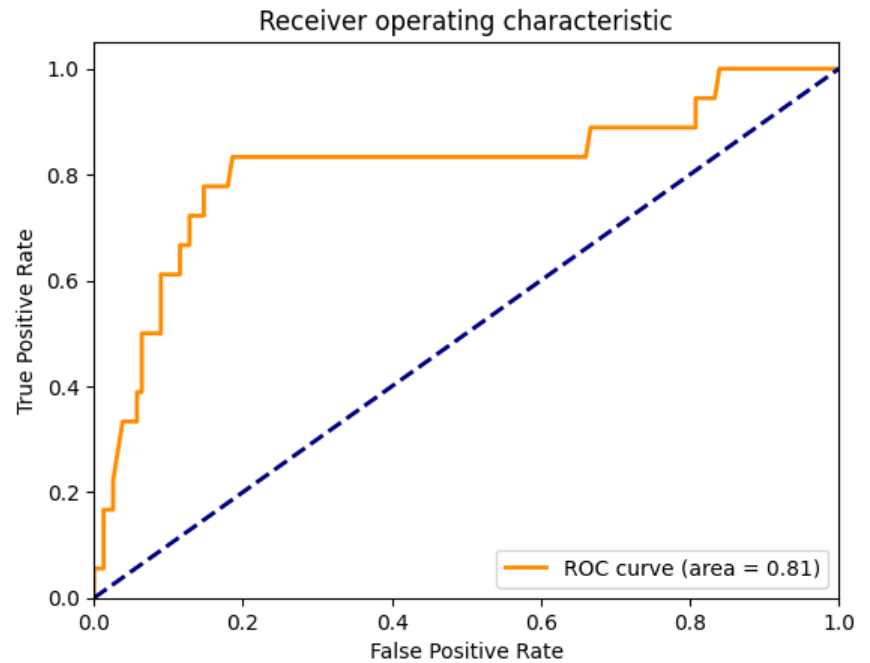
Experimental results



Model performance

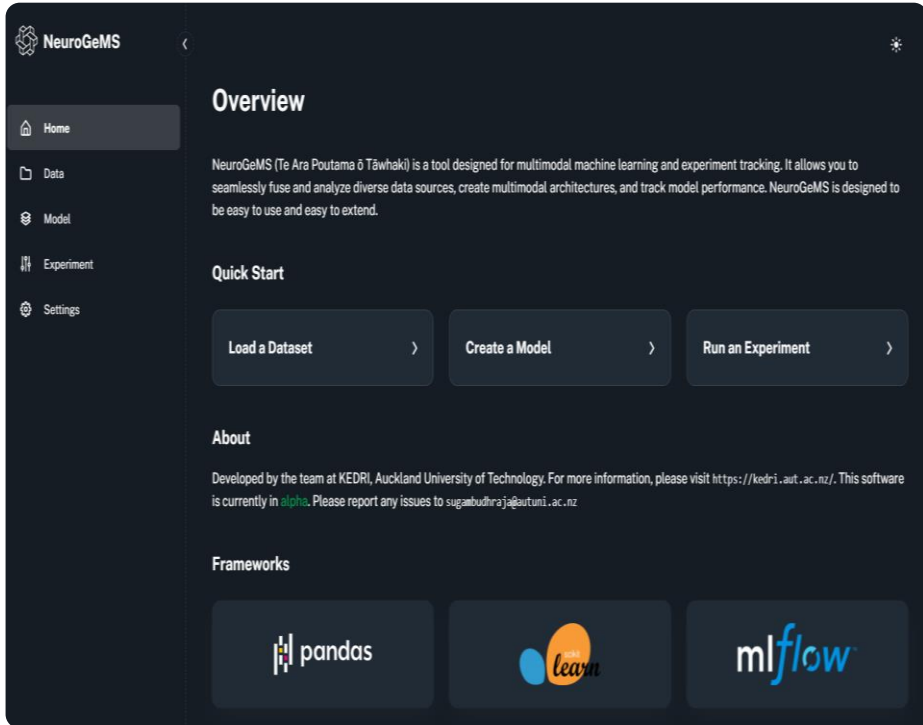
Predicting psychosis conversion within the next 12 months

Specificity: 0.782
Sensitivity: 0.833



NeuroGeMS

<https://kedri.aut.ac.nz/news-and-events/introducing-neurogems>



1. **Multimodal Fusion:** Effortlessly integrate data from diverse sources and modalities. NeuroGeMS empowers you to harness the full potential of your data and extract valuable insights through advanced fusion techniques.

2. **Interpretability:** Gain deeper understanding and build trust in your models with NeuroGeMS 's comprehensive interpretability module. Easily analyse and explain model decisions, making your AI applications more transparent and ethically sound.

3. **Efficient Dataset Management:** Organise and manage your datasets like a with NeuroGeMS' user-friendly tab for handling data. Seamlessly import, clean, and preprocess data to ensure the highest data quality for your experiments.

4. **Intuitive Model Creation:** NeuroGeMS provides a smooth workflow to create, customise and fine-tune machine learning models, accommodating both beginners and seasoned data scientists.

5. **Streamlined Experimentation:** Run, monitor, and save experiments with ease using NeuroGeMS 's smart experiment management feature. Spend less time on logistics and more time on innovation.

6. **Data Visualisation at Your Fingertips:** Visualize your data and model performance with NeuroGeMS 's interactive data visualisation tools. Gain valuable insights and communicate your findings more effectively.