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Brain-inspired Spiking Neural Network Architectures and Applications in Data Science and AI

Prof Nikola K Kasabov

Life Fellow IEEE, Fellow RSNZ, Fellow INNS College of Fellows

Doctor Honoris Causa, Obuda University, Budapest

George Moore Chair Professor of Data Analytics, Ulster University, the UK

Founding Director, KEDRI and Professor of Knowledge Engineering

Auckland University of Technology, Auckland, New Zealand

Guest Professor, IICT Bulgarian Academy of Sciences

Invited Professor, Peking University and Dalian University China

Honorary Professor, Teesside University UK, The University of Auckland NZ

Director, Knowledge Engineering Ltd., https://knowledgeengineering.ai

nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk https://academics.aut.ac.nz/nkasabov

Abstract

The talk discusses briefly current challenges in data science and artificial intelligence (AI) when dealing with spatio-temporal data, including: spatio-temporal learning (STL) and predictive modelling; spatio-temporal associative memories (STAM); interpretability and explainability; multiple modality of data; transfer learning, life-long learning. Opportunities to address these challenges are presented through advancement in Neuroinformatics, Neural networks and Neurocomputers (the 3N science areas).

The talk presents the main principles of evolving connections systems (ECOS) [1,2] , spiking neural networks (SNN) [3,4] and brain-inspired SNN computational architecture and demonstrates how they can be used to efficiently address the above data science and AI challenges. One of the SNN architectures, NeuCube, is used to demonstrate new data science and AI methods to deal with spatio temporal data, such as: STL; STAM; transfer learning; life-long learning; multimodal data.

Some experimental results include: predictive modelling of EEG, fMRI and other multimodal brain data; on-line learning of multisensory data for pollution and earthquake prediction; integrating financial time series and on-line news; and other. Implementations on neuromorphic hardware platforms are discussed along with future directions for data science and AI.

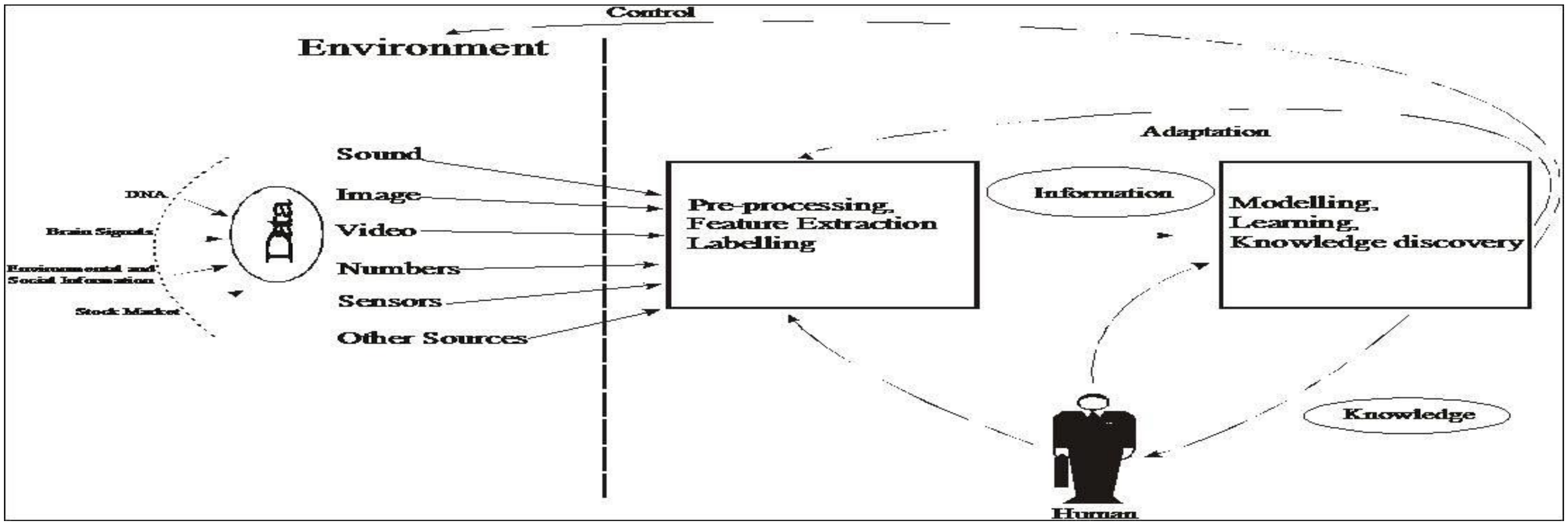
1. N.Kasabov, Evolving Connectionist Systems, Springer, 2007
2. NeuCom software
3. N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer, 2019.
4. NeuCube software

Content

1. Six challenges in Data science and AI.
2. The human brain as the most sophisticated STL and STAM machine
3. SNN and BI –SNN. NeuCube
4. Addressing the DS and AI challenges in BI-SNN
5. Some applications
6. Conclusions and future research

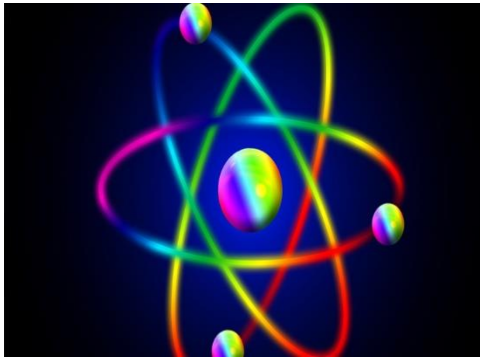
nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

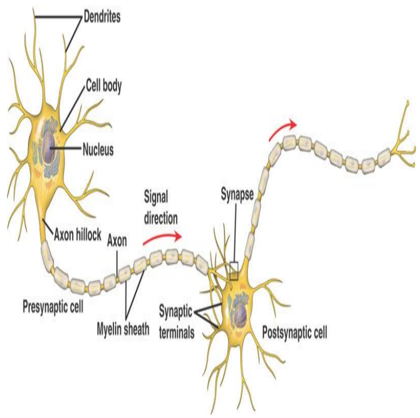
1. Six challenges in Data Science and AI

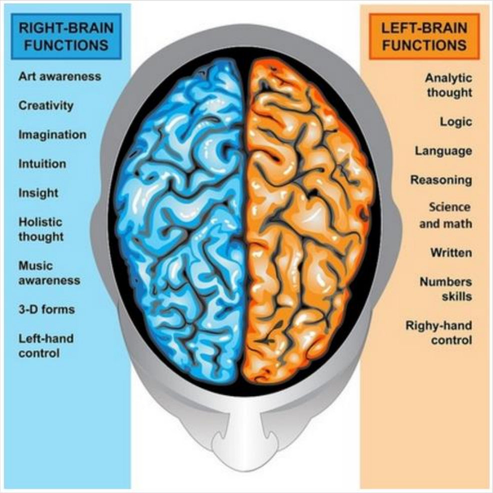


1. Spatio-temporal learning (STL) and predictive modelling;
2. Spatio-temporal associative memories (STAM);
3. Interpretability and explainability;
4. Transfer learning
5. Life-long learning
6. Multiple modality of data

Spatio-temporal learning (STL) and spatio-temporal associative memories (STAM)



The most important systems and processes in Nature are evolvable spatio-temporal. How do we model and explain them?

Spatio-temporal learning (STL) and spatio-temporal associative memory (STAM)

Spatio-temporal learning (STL) is when existing spatial or other relevant information from the data is used to structure a model and then temporal information is used to train the model. The model captures evolvable and explainable spatio/specro temporal patterns.

A STAM is a machine learning model that is trained on a full set of spatio-temporal variables, but can be successfully recalled on only a subset of the variables measured in different time intervals. In addition, a STAM-SNN model can be further incrementally trained on a new subset of variables measured at varying times.

A STAM model is validated through the introduced association- and generalization accuracy. Departing from traditional deep neural networks and machine learning methods, where trained models can only be recalled or incrementally trained on the same set of variables using vector-based representation, STAM opens the field of machine intelligence for the development of large-scale global spatio-temporal models that can be recalled and used locally, within the available local spatio-temporal data. Possible applications for STAM-SNN include: biological and brain signals; audio-visual data; seismic sensory data; financial and economic data; and other.

Kasabov, N (2023). STAM-SNN: Spatio-Temporal Associative Memories in Brain-inspired Spiking Neural Networks: Concepts and Perspectives. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.23723208.v1

2. The human brain as the most sophisticated STL and STAM machine

The brain (80bln neurons, 100 trillions of connections, 200 mln years of evolution) is the ultimate learning machine

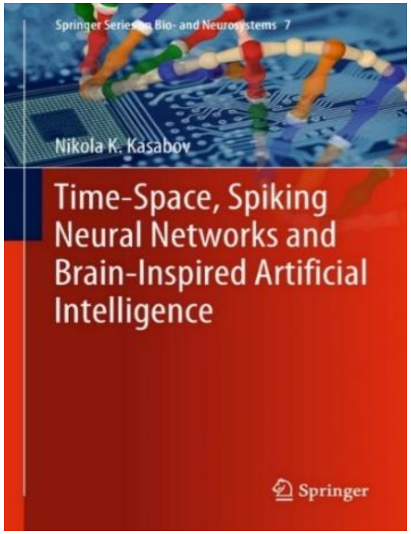
Three, mutually interacting, spatial memory types:

- short term (membrane potential);
- long term (synaptic weights);
- genetic (genes in the nuclei).

Temporal data at different time scales:

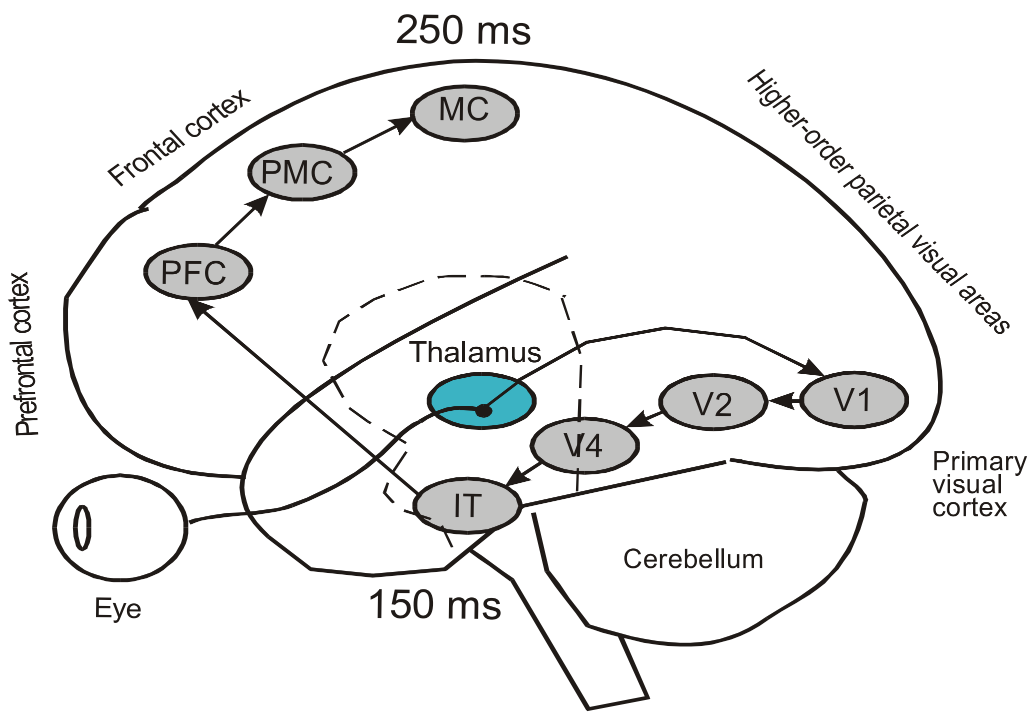
- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

Knowledge is represented as deep **spatio-temporal patterns** that can evolve/adapt over time.



Kasabov, N., Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019), https://www.springer.com/gp/book/9783662577134

Knowledge of seeing an object and grasping it is learned incrementally as an **evolvable spatio-temporal trajectory** of connections between clusters of neurons in the brain

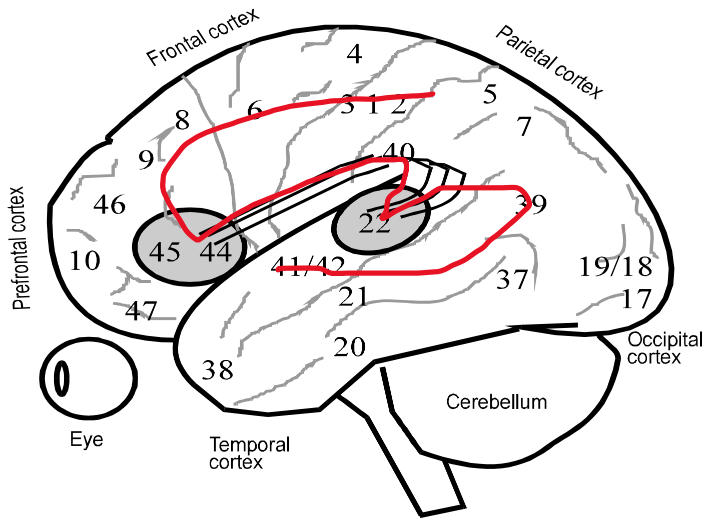


Deep serial processing of visual stimuli in humans for image classification and action.

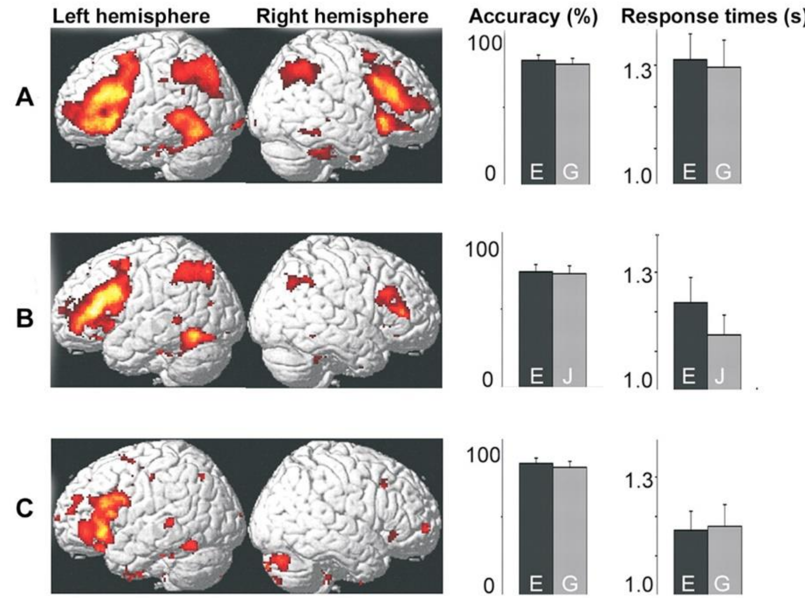
Location of cortical areas: V1 = primary visual cortex, V2 = secondary visual cortex, V4 = quartiary visual cortex, IT = inferotemporal cortex, PFC = prefrontal cortex, PMC = premotor cortex, MC = motor cortex.

L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007

STL and STAM of speech and language



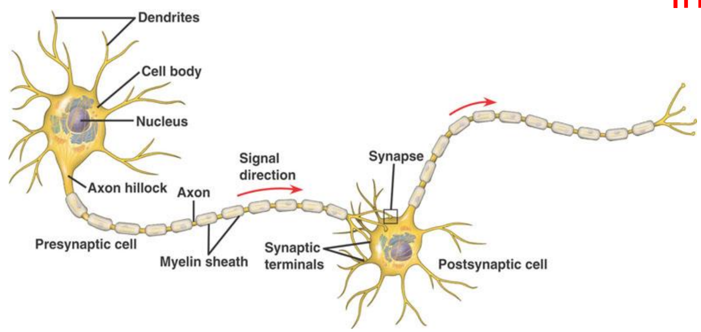
(from L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007)

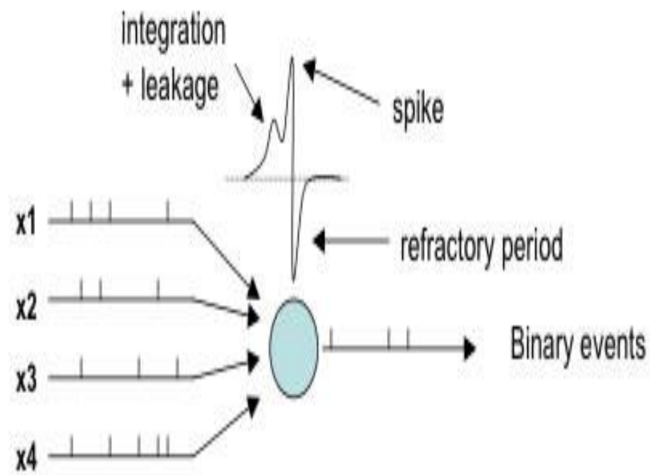


Common brain activation areas in bilingual subjects (Crinion et al, Science, 2006)

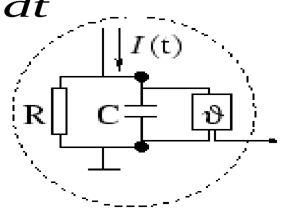
The basic model of language processing during the simple task of repeating the word that has been heard is the Wernicke-Geschwind model (Mayeux and Kandel 1991). A language task involves transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (Brodmann’s area 41), then to the higher-order auditory cortex (area 42), before it is relayed to the angular gyrus (area 39). From here, the information is projected to Wernicke’s area (area 22) and then, by means of the *arcuate fasciculus*, to Broca’s area (44, 45), where the perception of language is translated into the grammatical structure of a phrase and where the memory for word articulation is stored. This information about the sound pattern of the phrase is then relayed to the facial area of the motor cortex that controls articulation so that the word can be spoken.

3. **Spiking Neural Networks (SNN) and Brain-inspired SNN architectures**





$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$



Information processing principles in neurons and neural networks:

- Trains of spikes
- Time, frequency and space
- Synchronisation and stochasticity
- Evolvability…

Spiking neural networks (SNN)

- Leaky Integrate-and-fire
- Probabilistic model
- Neurogenetic model

They offer the potential for:

- Spatio-temporal data processing
- Bridging higher level functions and “lower” level genetics
- Integration of modalities

SNN open the field of brain-inspired (cognitive, neuromorphic) computing.

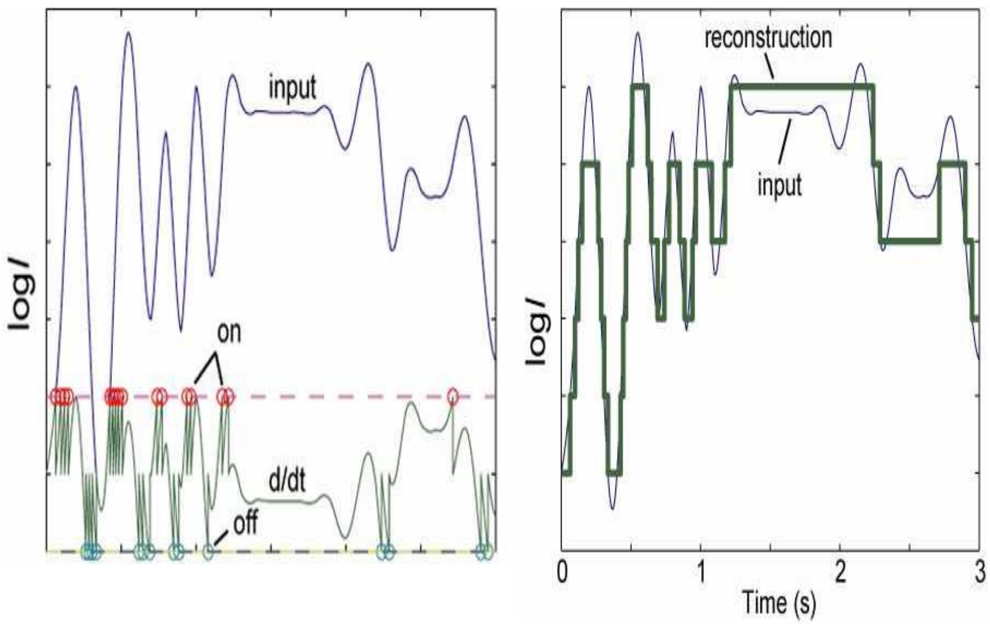
“*The goal of brain-inspired computing is to deliver a scalable neural network substrate while approaching fundamental limits of time, space, and energy,*” IBM Fellow **Dharmendra Modha**, chief scientist of Brain-inspired Computing at IBM Research,

Spike encoding methods for STL

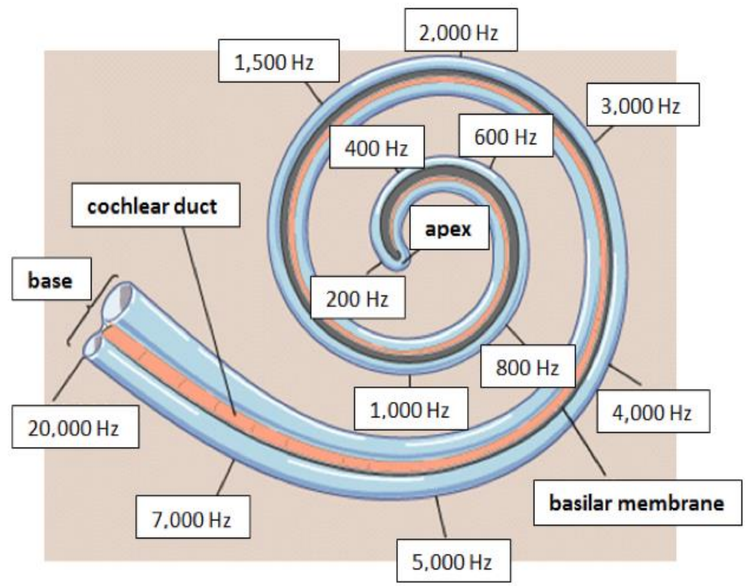
A spike is generated only if a change in the input data occurs beyond a threshold

Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128: Retinotopic

Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich): Tonotopic



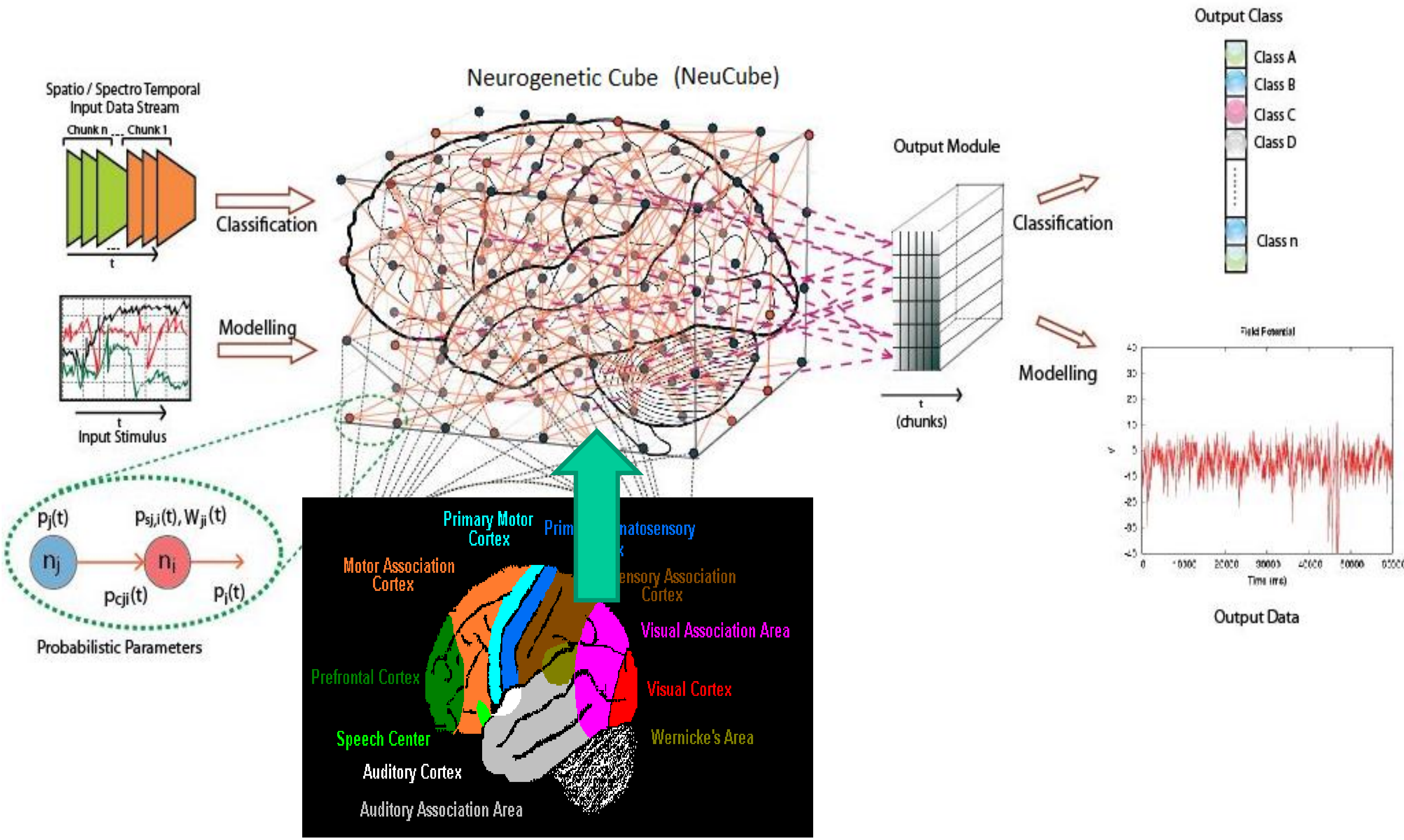
Threshold-based encoding – retinotopic mapping for spatio-temporal data



Tonotopic organization of the cochlea for spectro-temporal data

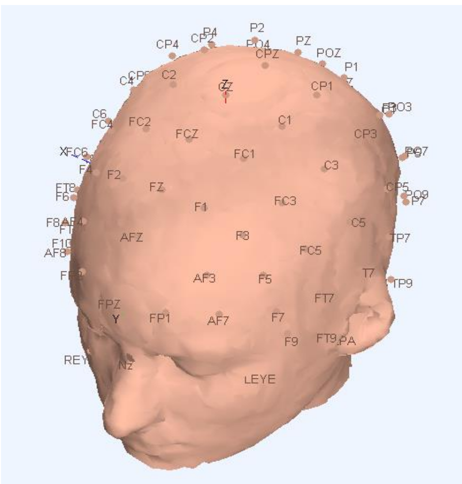
https://sites.google.com/site/jayanthinyswebite

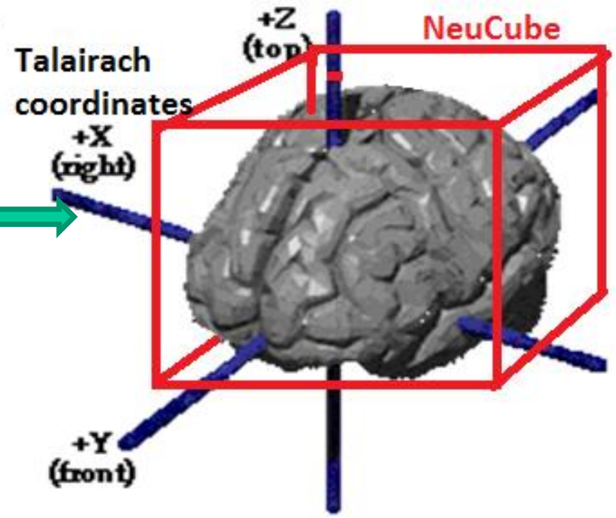
BI-SNN: The NeuCube Architecture for STL (3D space + 1D time)

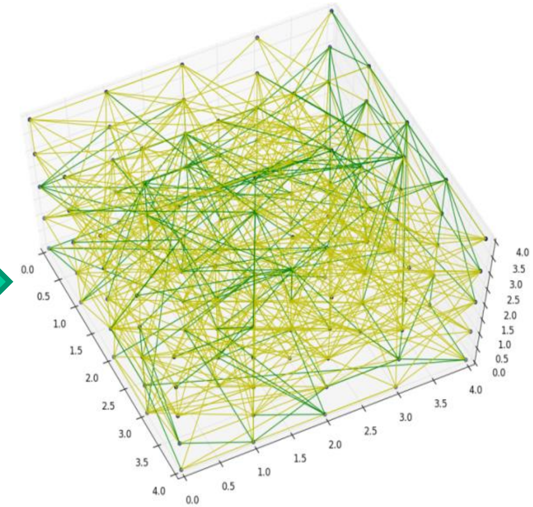


Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

Spatio-temporal mapping of brain data into a 4D SNNcube for STL







Further development of ideas from SOM (Kohonen) and ART (Grossberg)

E. Tu, N. Kasabov, J. Yang, Mapping Temporal Variables into the NeuCube Spiking Neural Network Architecture for Improved Pattern Recognition and Predictive Modelling, IEEE Trans. on Neural Networks and Learning Systems, 28 (6), 1305-1317,, 2017 DOI: 10.1109/TNNLS.2016.2536742, 2017.

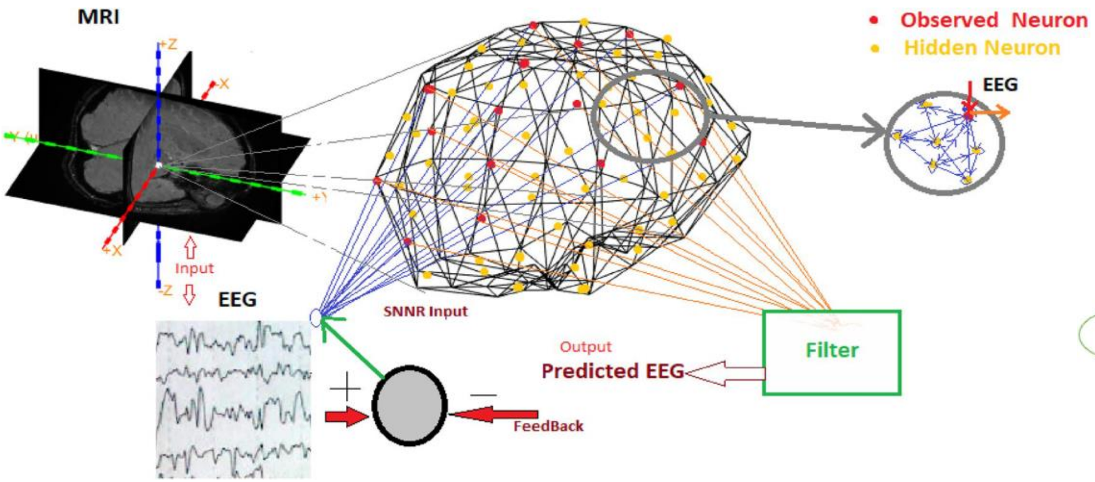
Different templates can be used to **spatially structure** a SNN to enable STL

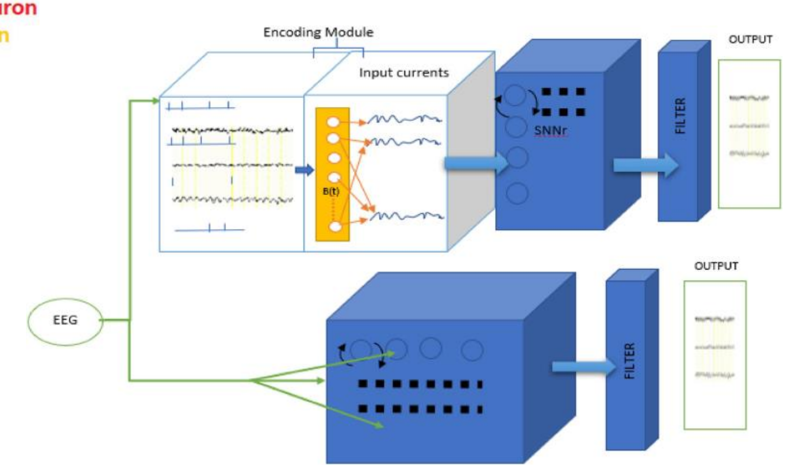
Spatial templates (e.g. brain Talairach, MNI, MRI, etc.; geographical maps; molecular structure; quantum)

Temporal aspect - Learning: Using encoded vs real value signals

Example: Personalised MRI structured BI-SNN and learning algorithms for personalized modelling, analysis, and prediction of EEG signals, S Saeedinia, MJahed-Motlagh, ATafakhori & N Kasabov, *Scientific Reports,* **11**,12064 (2021)

Training the SNN to predict the signals on the input neurons → As a result of the spatial location of the neurons, all of them can also predict their spiking activities!!

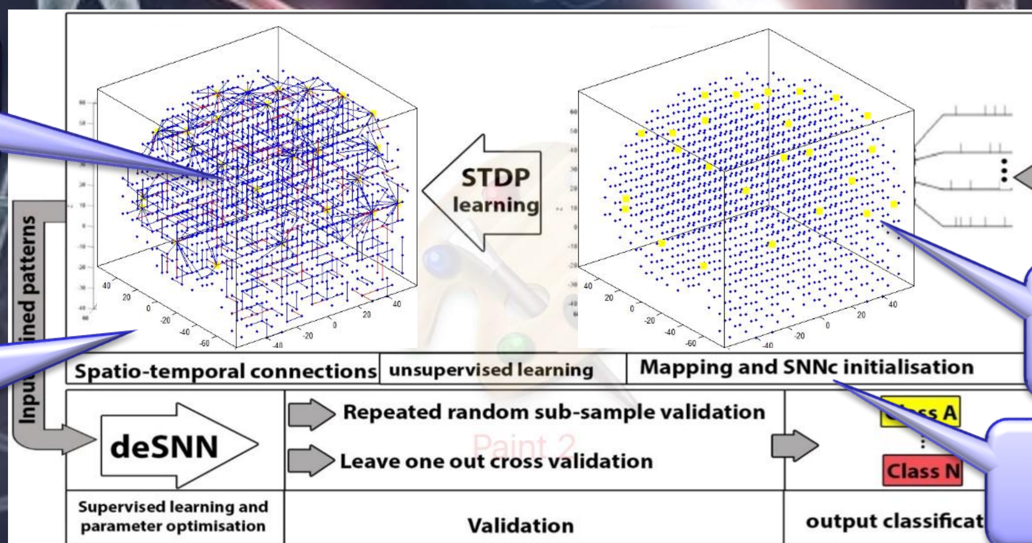




eSTL in NeuCube

Creation of Neuron Connections During The Learning

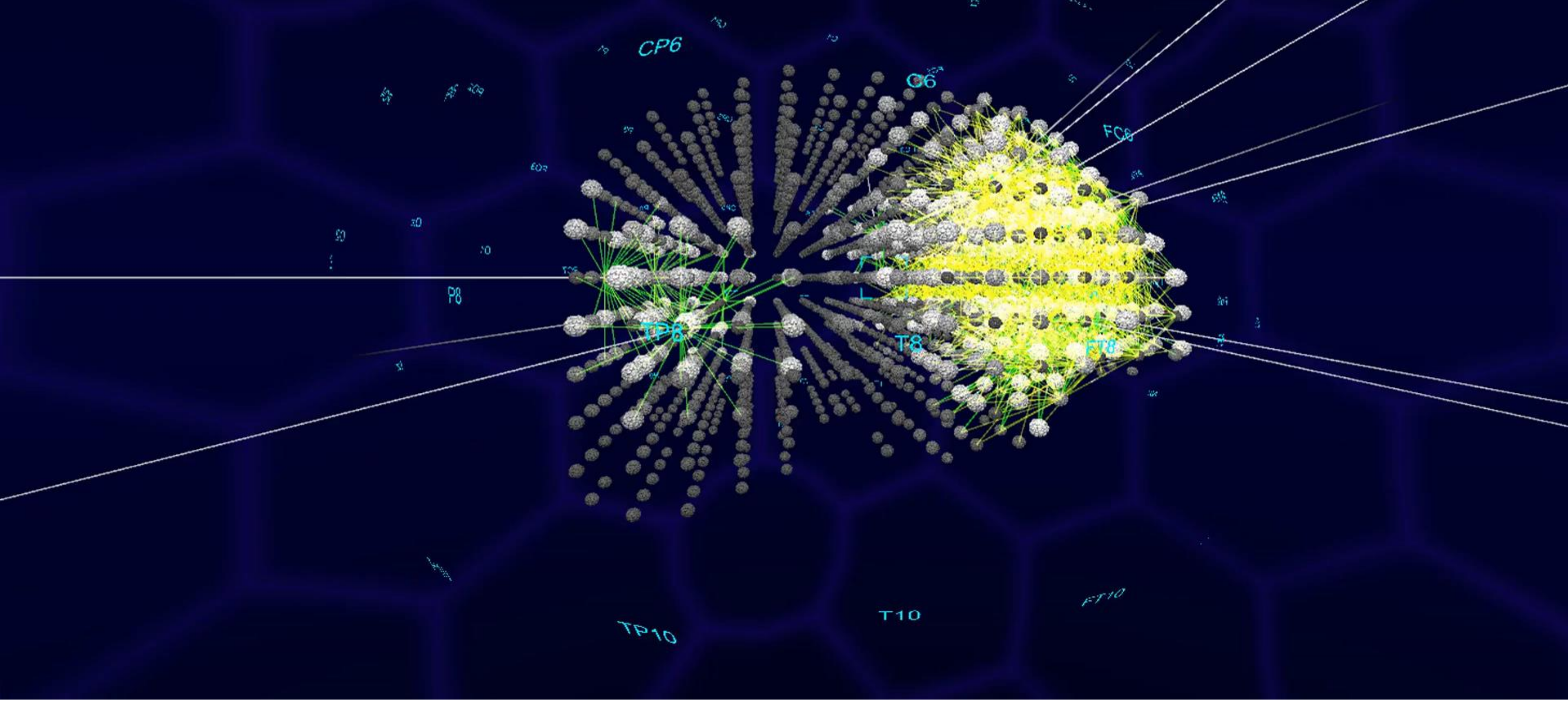
The More Spike Transmission, The More Connections Created



Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning

STL in NeuCube

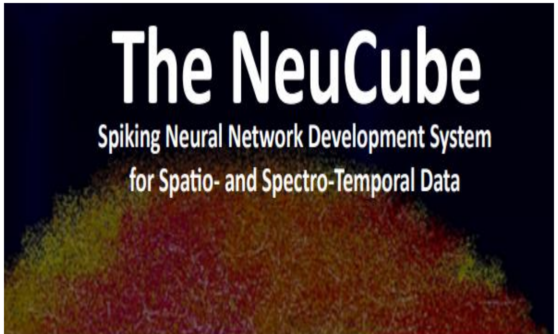


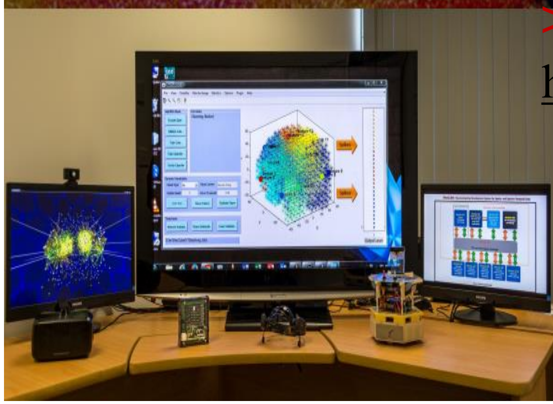
N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, v.78, 1-14, 2016. http://dx.doi.org/10.1016/j.neunet.2015.09.011.

NeuCube development environment for SNN system design can also include a neuromorphic hardware (e.g. SpiNNaker, Loihi)

nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

NeuCube Implementations





> **NeuCubeM2:** Extended NeuCube
https://kedri.aut.ac.nz/research-groups/neucube.

> **NeuCubePy:** Python implementation of NeuCube
https://kedri.aut.ac.nz/news-and-events/introducing-neucube-python

> **NeuCube in PyNN** to work on SpiNNaker: https://github.com/behrenbeck/NeuCube_SpiNNaker.

> NeuCube visualisation as a brain-inspired mode: https://www.youtube.com/watch?v=E7XO10TVaK0

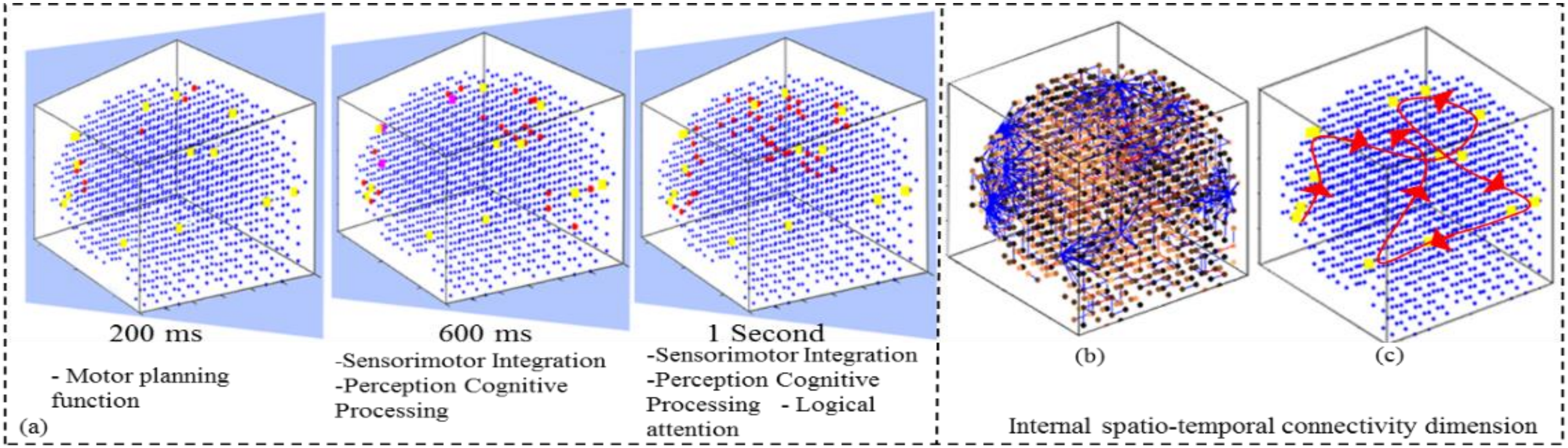
> **NeuroGeMS:** A novel NeuroGenetic Multimodal modelling System for personalised modelling and early disease prediction (**Te Ara Poutama ō Tāwhaki**)

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

4. **Addressing the DS and AI challenges in a BI-SNN**

Spatio-temporal learning

A SNNcube that learns EEG data from 14 EEG channels when a person is moving a wrist. The sequence of connections of the trained SNNcube can be interpreted as TSR. The figure is showing only few aggregated events (out of 1000, one at each millisecond EEG data).



TSR representation of time and space aggregated events:

IF (a person is moving a hand up)

THEN (the following brain functions are activated in space and time):

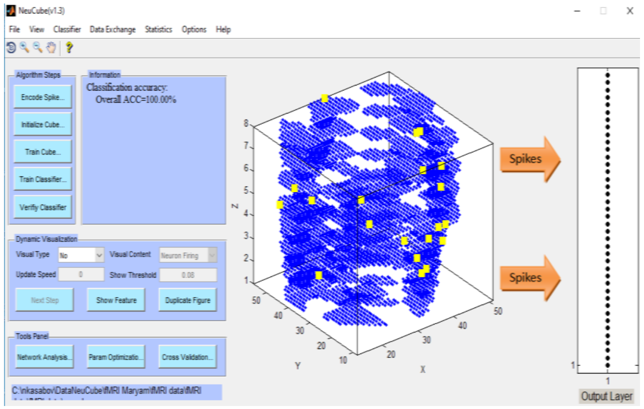
E1: Planning, in the Motor Planning functional brain area, time T1,

AND E2: Sensorimotor integration, in the Sensorimotor integration brain area, at time T2

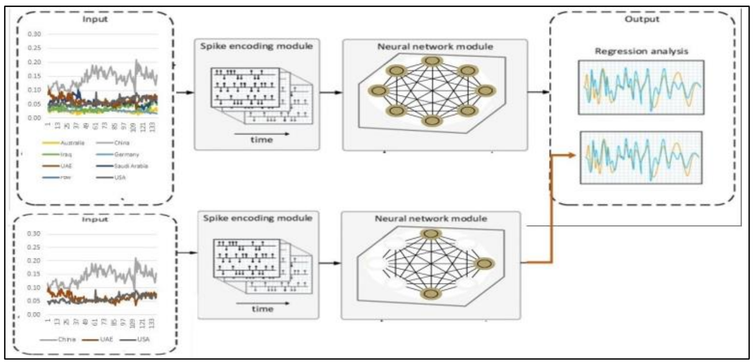
AND E3: Perception, in the Perception Cognitive brain area, time T3

AND E4: Attention, in the Logical Attention brain area, time T4.

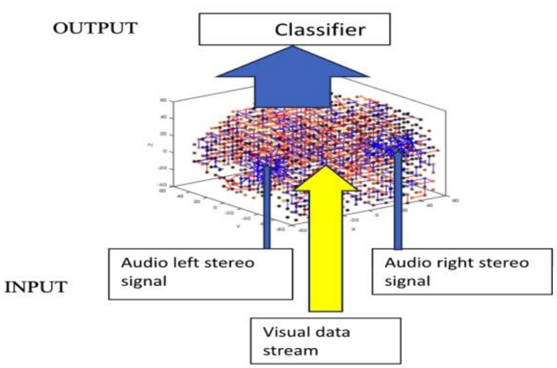
Spatio-temporal associative memories (STAM)



N. Kasabov, H. Bahrami, M. Doborjeh, and A. Wang, "Brain inspired spatio-temporal associative memories for neuroimaging data: EEG and fMRI, MDPI Bioengineering, 2023. [Online]. Available: https://doi.org/10.20944/preprints202308.0333.v1



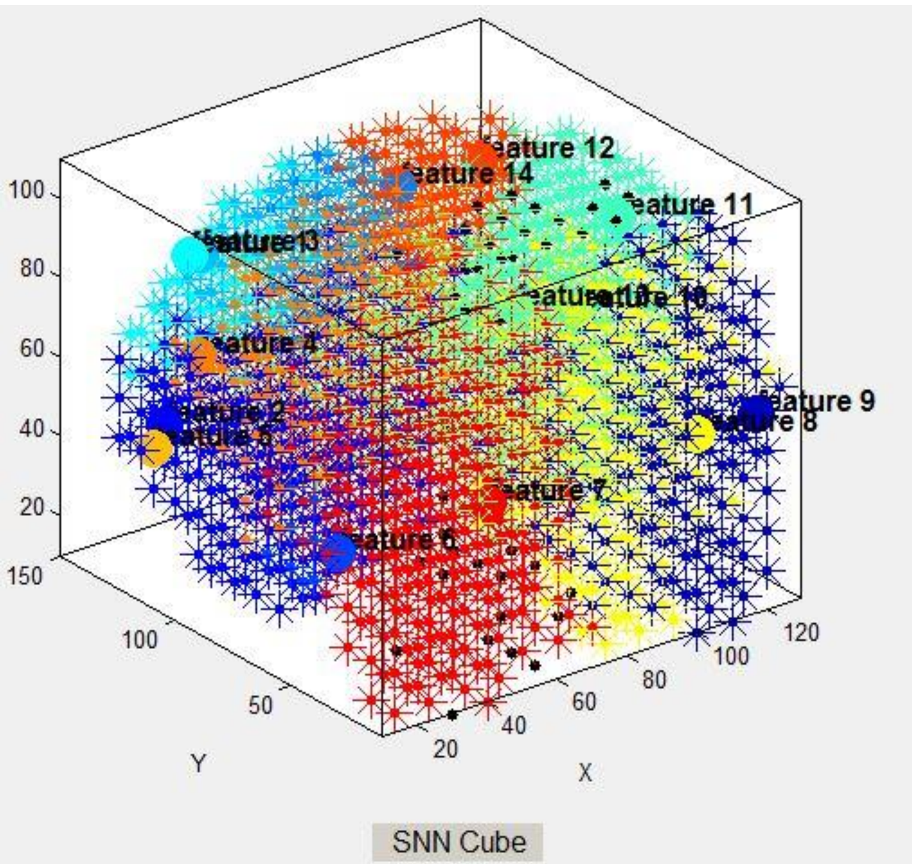
I. AbouHassan, N. Kasabov, T. Bankar, R. Garg, and B. S. Bhattacharya, "PAMeT –SNN : Predictive associative memory for multiple time series based on spiking neural networks with case studies in economics and finance," TechRxiv, 9 2023, preprint. [Online]. Available: https://doi.org/10.36227/techrxiv.24063975.v1

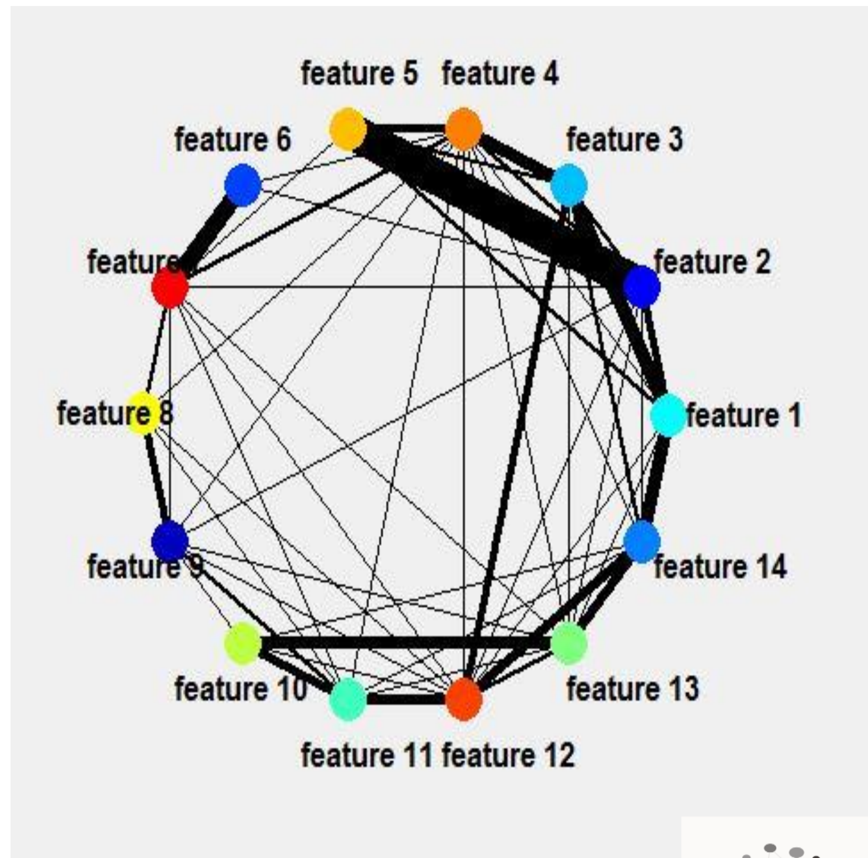


N.Kasabov, B.Bhattacharya, et al, AViAM-SNN: A Framework for Audio-Visual Associative Memories using Brain-inspired Spiking Neural Networks, IEEE Tr NNLS, 2023 (submitted)

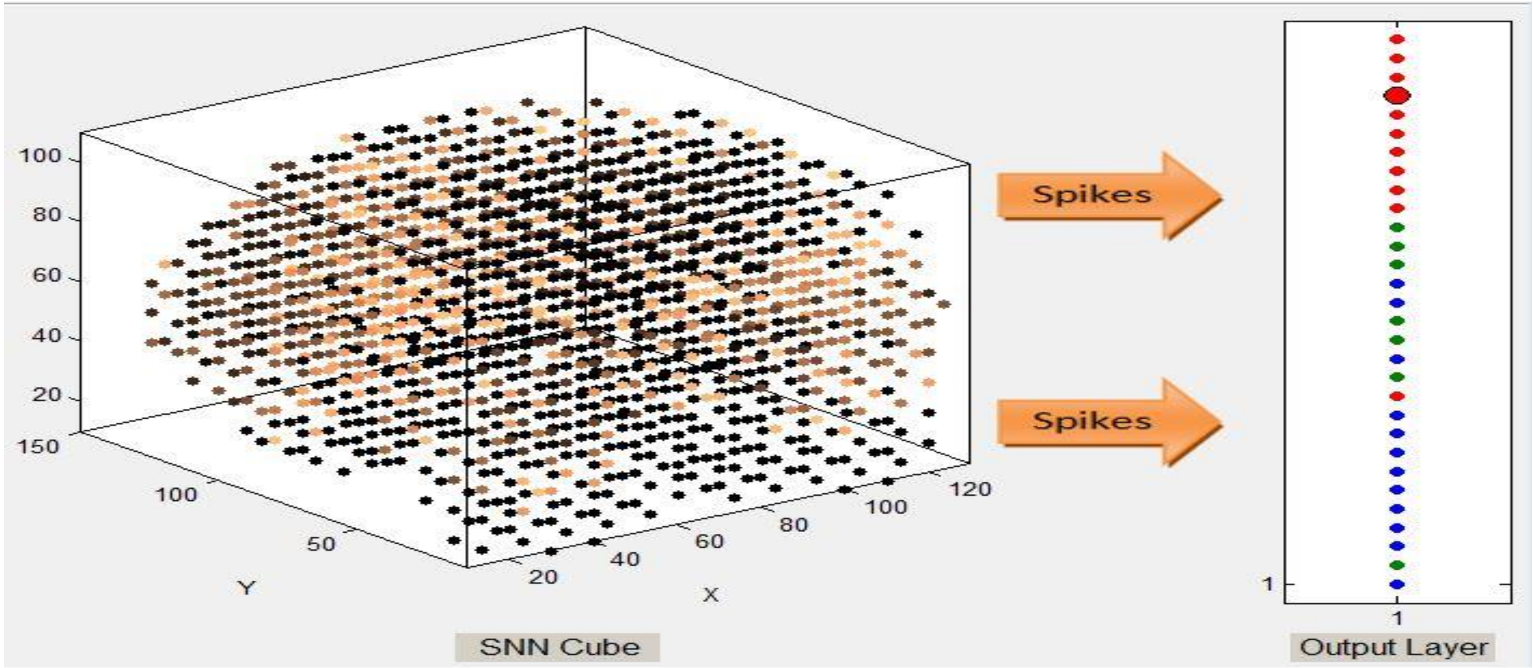
Interpretabiliuty and explainability in a NeuCube model

- Clusters of highly connected neurons to input neurons;
- Clusters of spiking activity spread from input neurons ;
- A dynamic graph of information exchange between spatially distributed clusters around the inputs (Feature Interaction networks)





Interpretability and explainability: Extracting fuzzy spatio-temporal rules



Example of TSR representation in a trained SNN classifier

IF (area (Xi,Yi,Zi) in the Cube with a cluster radius Ri is activated at time about T1) AND

(area (Xj,Yj,Zj) with a cluster radius Rj is activated at time about T2) AND

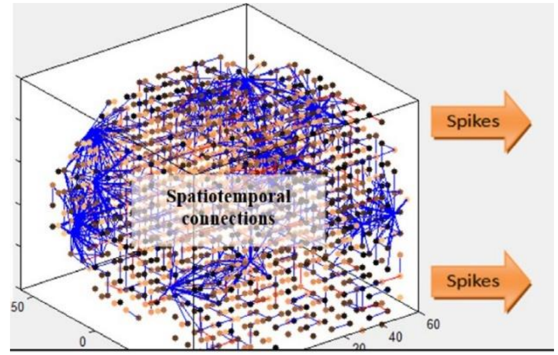
(area (Xk,Yk,Zk) with a cluster radius Rk is activated at time about T3) AND

(no other areas of the SNNcube are activated)

THEN (The output class prototype is number 4 from class 1).

A biologically relevant fuzzy spatio-temporal rule (fSTR) can be extracted from a trained NeuCube on EEG data representing one movement of a subject (GAL)

IF (event E1 at about location S1 and about time T1) AND (event E2 ……..) … THEN (Action)



IF$(E_{\text{cue-onset}} : F_{\text{cue-onset}}, S\{\text{cue-onset}\}, t_{\text{cue-onset}}, P>0.8)$
$AND(E_{\text{motor-planning}} : F_{\text{motor-planning}}, S_{\text{motor-planning}}, t_{\text{motor-planning}}, P>0.8)$
$AND(E_{\text{movement-onset}} : F_{\text{movement-onset}}, S_{\text{movement-onset}}, t_{\text{movement-onset}}, P>0.8)$
$AND(E_{\text{touch-object}} : F_{\text{touch-object}}, S_{\text{touch-object}}, t_{\text{touch-object}}, P>0.8)$
$AND(E_{\text{hold-object}} : F_{\text{hold-object}}, S_{\text{hold-object}}, t_{\text{hold-object}}, P>0.9)$
$AND(E_{\text{release-object}} : F_{\text{release-object}}, S_{\text{release-object}}, t_{\text{release-object}}, P>0.8)$
$AND(E_{\text{rest}} : F_{\text{rest}}, S_{\text{rest}}, t_{\text{rest}}, P>0.8)$
THEN$(Q = Q_{\text{grasp-and-lift}})$.

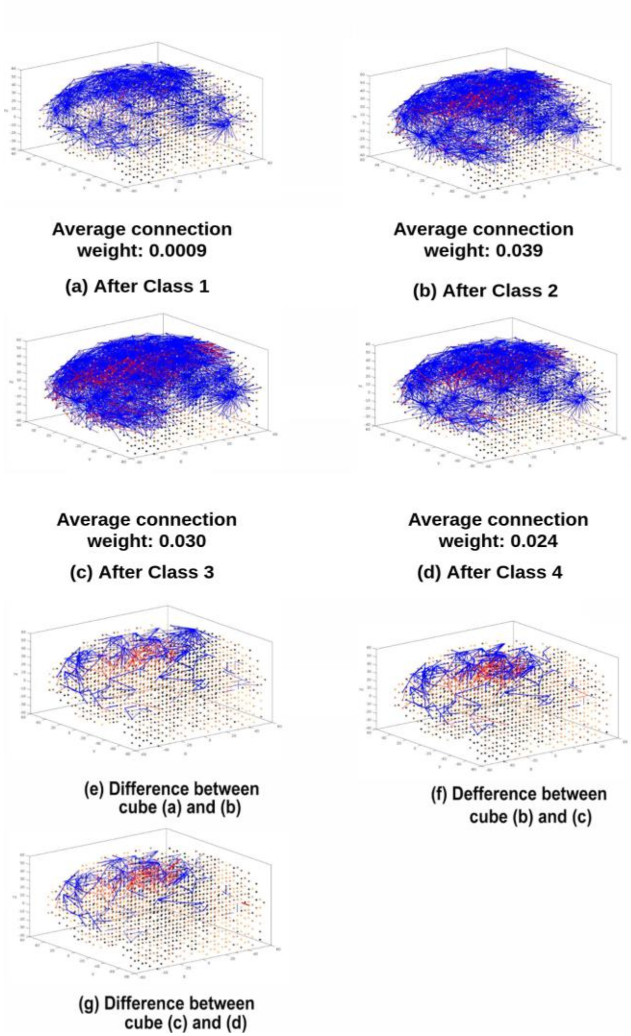
where Si = {Posterior Lobe, Temporal Lobe, Limbic Lobe, Frontal Lobe, Anterior Lobe, Occipital Lobe, Midbrain, Parietal Lobe}

K.Kumarasinghe, N.Kasabov, D.Taylor, Deep Learning and Deep Knowledge Representation in Spiking Neural Networks for Brain-Computer Interfaces, Neural Networks, vol.121 (2020),169-185, doi: https://doi.org/10.1016/j.neunet.2019.08.029.

Kasabov, N., Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019), 750p., https://www.springer.com/gp/book/9783662577134

Transfer learning of fuzzy spatio-temporal rules in NeuCube

N.K. Kasabov, Tan, Yongyao Tan; Doborjeh, Maryam; Tu, Enmei; Yang, Jie (2023): Transfer Learning of Fuzzy Spatio-Temporal Rules in the NeuCube Brain-Inspired Spiking Neural Network: A Case Study on EEG Spatio-temporal Data. IEEE Transactions of Fuzzy Systems, 2023.



Average connection weight: 0.0009

(a) After Class 1

Average connection weight: 0.039

(b) After Class 2

Average connection weight: 0.030

(c) After Class 3

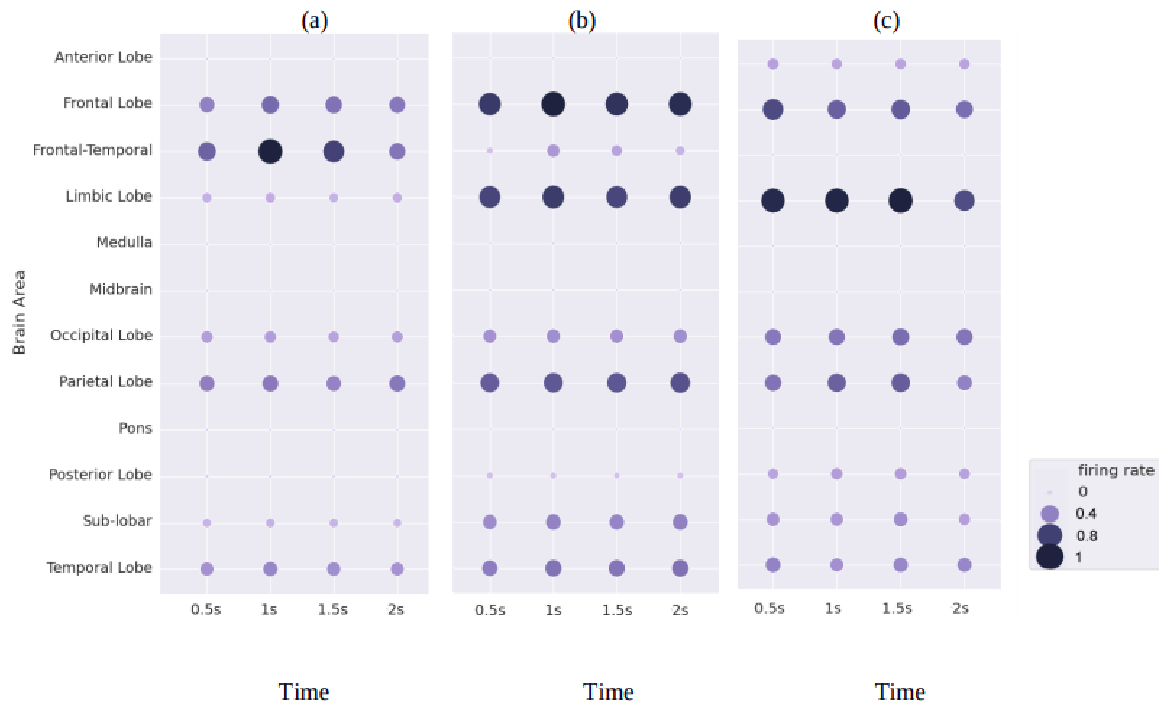
Average connection weight: 0.024

(d) After Class 4

(e) Difference between cube (a) and (b)

(f) Defference between cube (b) and (c)

(g) Difference between cube (c) and (d)



FSTR for (a):

IF (firing rate of $area_{1,1}(t1)$ is SMALL and $area_{2,1}$ $(t1)$ is MEDIUM (at time t1 about 0.5s) AND

AND (firing rate of $area_{1,2}(t2)$ is SMALL and $area_{2,2}(t2)$ is MEDIUM and $area_{3,2}(t2)$ is HIGH (at time t2 bout 1s)

AND (firing rate of $area_{1,3}(t3)$ is SMALL and $area_{2,3}(t3)$ is MEDIUM (at time t3 about 1.5s)

AND (firing rate of $area_{1,4}(t4)$ is SMALL and $area_{2,4}(t4)$ is MEDIUM (at time t4 about 2s)

THEN (This is the transfer of knowledge (the difference) in the SNNcube activity after it was trained on task 2 after task 1)

Note: Task 1: Reach for a glass of water, drink, and place the glass on the table. ;

Task 2: Throw a ball from the right hand to the left hand.

nkasabov@aut.ac.nz

Life-long STL in NeuCube

- How is life-long STL performed in the brain?

D Kudithipudi et al H.Siegelman, Biological underpinnings for lifelong learning machines, NatMI, vol.4,2022

Neurogenesis
Neuromodulation
Episodic replay
Metaplasticity
Multisensory integration

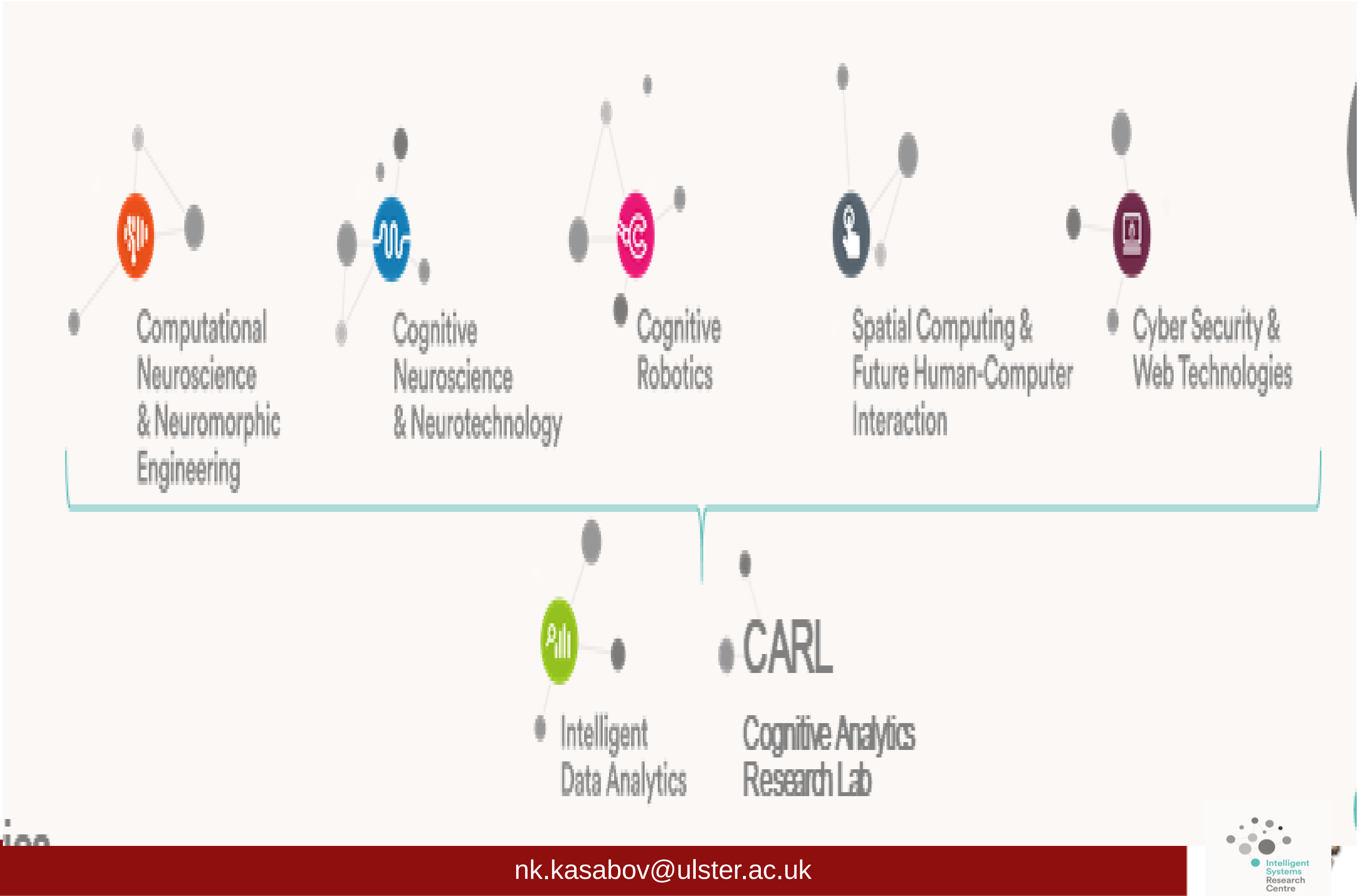
- How life-long STL can be achieved in ANN?

G.I. Parisi, R.Kemker, J. L. Part, C. Kanan, S.Wermter, Continual lifelong learning with neural networks: A review, Neural Networks, 113, 2019, 54-71

- How can life-long be implemented in BI-SNN?

Spike-frequency or spike-time predictive modelling at single neurons using error backpropagation
Neuromodulatory synaptic connection
Weight regulation
Homeostasis
Lyapunov energy function
Evolving classifiers/regressors (deSNN) where neuronal outputs are evolved and aggregated continuously

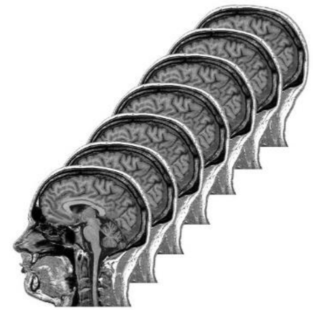
5. Applications

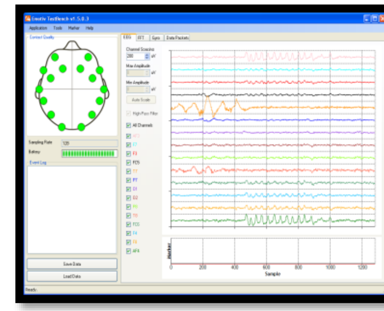


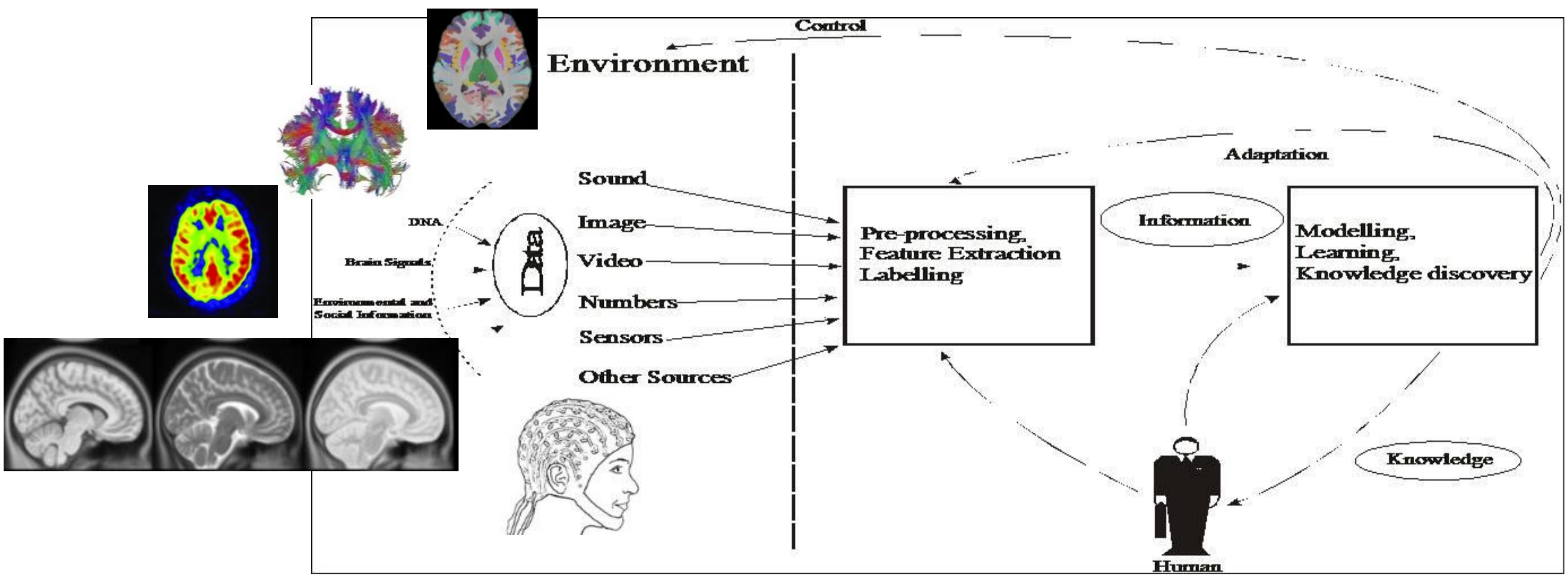
nk.kasabov@ulster.ac.uk

STL for multiple modality of data

- different spatial scales
- different time scales



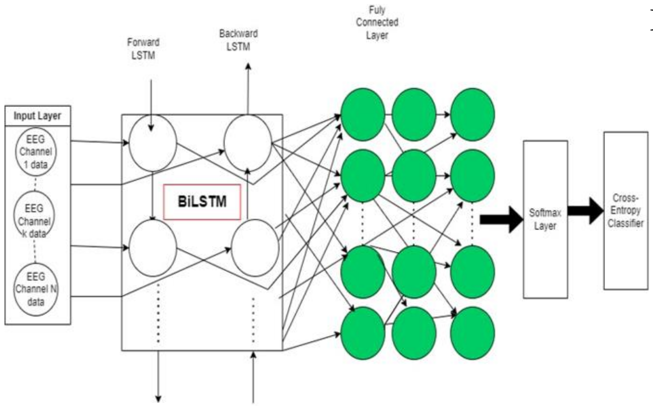


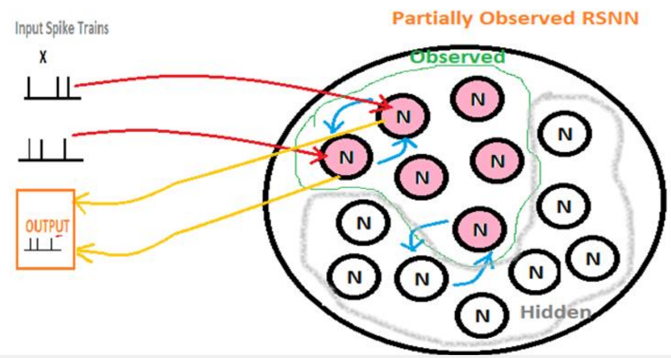


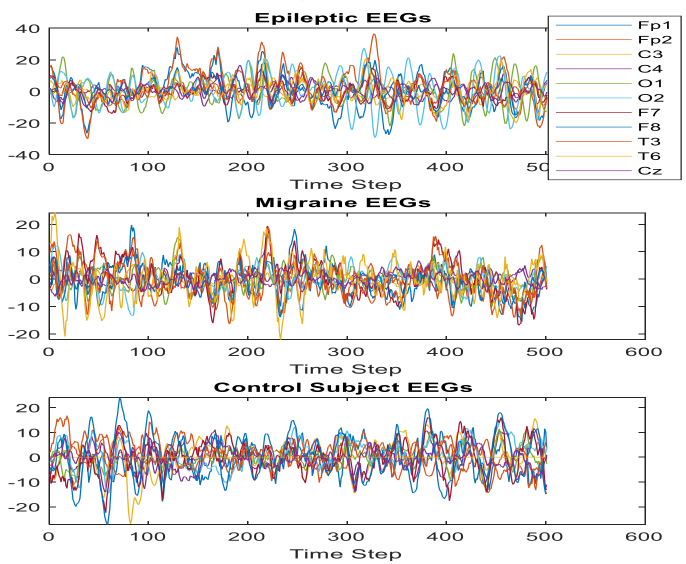
Higher classification accuracy of brain EEG data and biomarker discovery

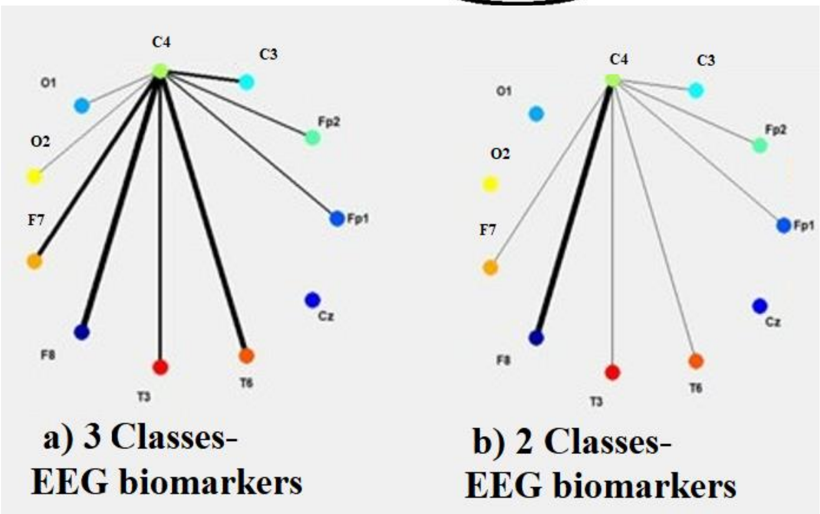
S. Saeedinia, M.Reza Jahed- Motlagh, A. Tafakhori, N. K. Kasabov, Diagnostic biomarker discovery from brain EEG data with LSTM, reservoir-SNN and NeuCube: Methods and a pilot study on epilepsy vs migraine, submitted to SREP, https://www.techrxiv.org/, June 2023.

LSTM: 90%; RSNN: 85%; NeuCube: 97%



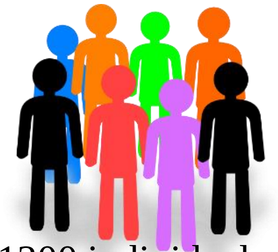






Personalised predictive modelling of individual risk of stroke

How environmental risk factors can influence the risk of individual stroke occurrence?



>1200 individuals

Stroke (2011-2012)

Clinical records (37 variables)

10 environmental (CO, NO2, O3, SO2, and PM10, PM2.5, temperature, wind-direction average, wind-speed, and solar radiation).

Affected group of 169 individuals: (45% female); 55% male; mean-age= 74.05> mean-age non-affected group (70.4); had *history of stroke* in close family member, *overweight*, *older*, *smokers*, *diabetic*, and taking *medication*.

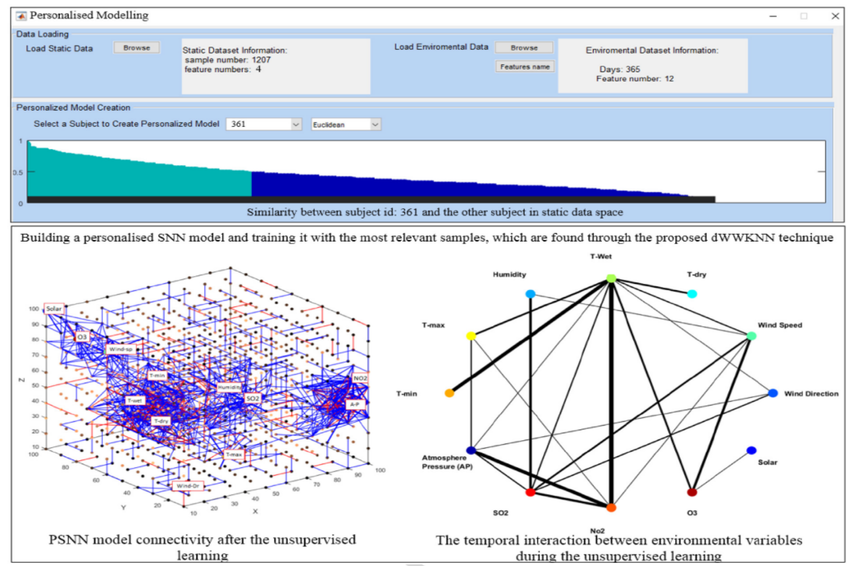


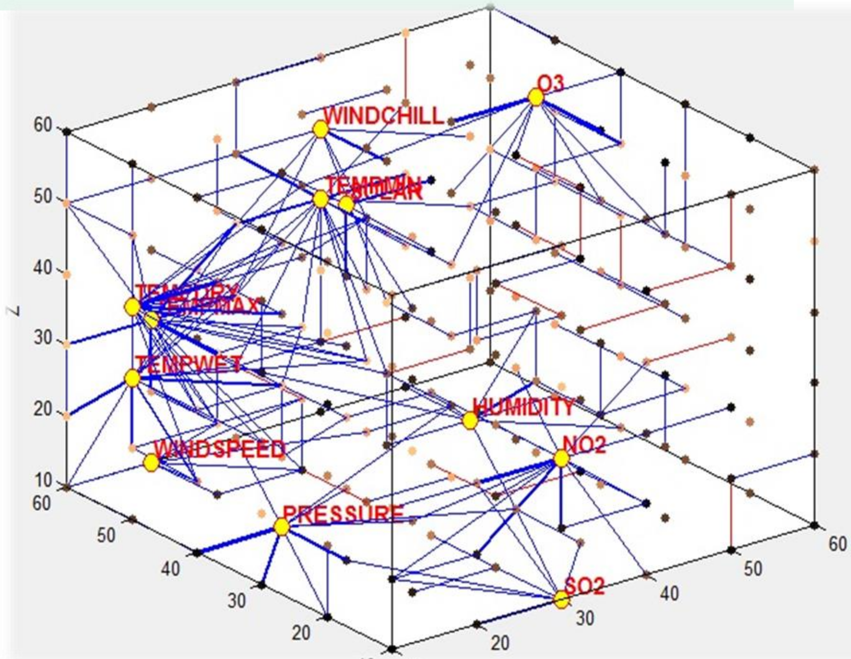
Fig. 9. The user interface of the proposed personalised predictive system for prediction of risk of stroke. A PSNN model is created to spatially map the environmental variables, where the most correlated variables are mapped to closer input neurons. Then the PSNN model was trained on the temporal spike sequences using STDP unsupervised learning to adapt the model connections. Blue lines represent excitatory synapses (positive connections), whereas red lines refer to inhibitory synapses (negative connections). In the graph, the amount of spike communication between clusters of neurons, centred by input variables, is captured as the thickness of lines. The thicker the line, the more interactions between variables during STDP learning.

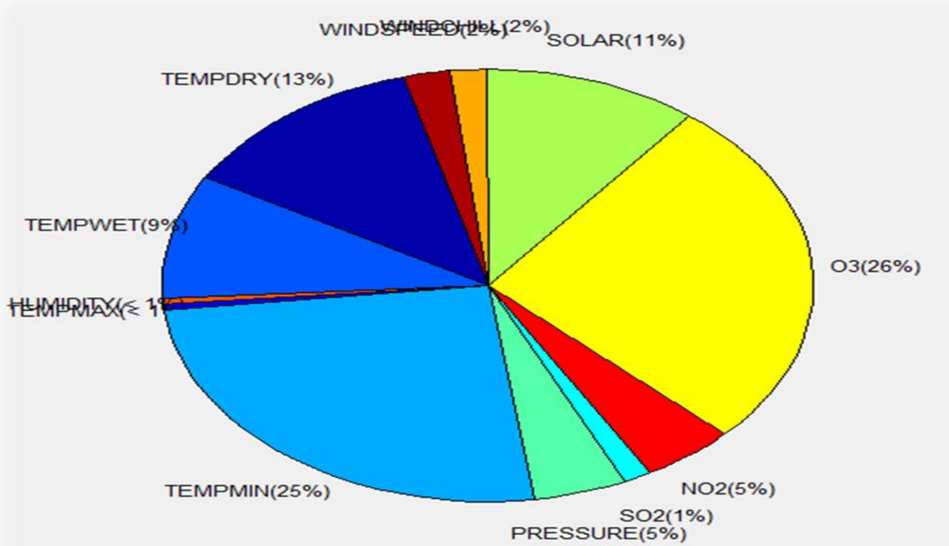
Maryam Doborjeh, Zohreh Doborjeh, Alexander Merkin, Rita Krishnamurthi, Reza Enayatollahi, Valery Feigin, **Nikola Kasabov**, Personalised Spiking Neural Network Models of Clinical and Environmental Factors to Predict Stroke, Cognitive Computation, COGN-D-20-00511R2, 26 , 2021, https://www.springer.com/journal/12559.

Personalised prediction of risk for stroke days ahead

(N.Kasabov, M. Othman, V.Feigin, R.Krishnamurti, Z Hou et al - Neurocomputing 2014)

METHODS	SVM	MLP	KNN	WKNN	NEUCUBE[ST]
1 day earlier (%)	55 *(70,40)*	30 *(50,10)*	40 *(50,30)*	50 *(70,30)*	**95** ***(90,100)***
6 days earlier (%)	50 *(70,30)*	25 *(20,30)*	40 *(60,20)*	40 *(60,20)*	**70** ***(70,70)***
11 days earlier (%)	50 *(50,50)*	25 *(30, 20)*	45 *(60,30)*	45 *(60,30)*	**70** ***(70,70)***



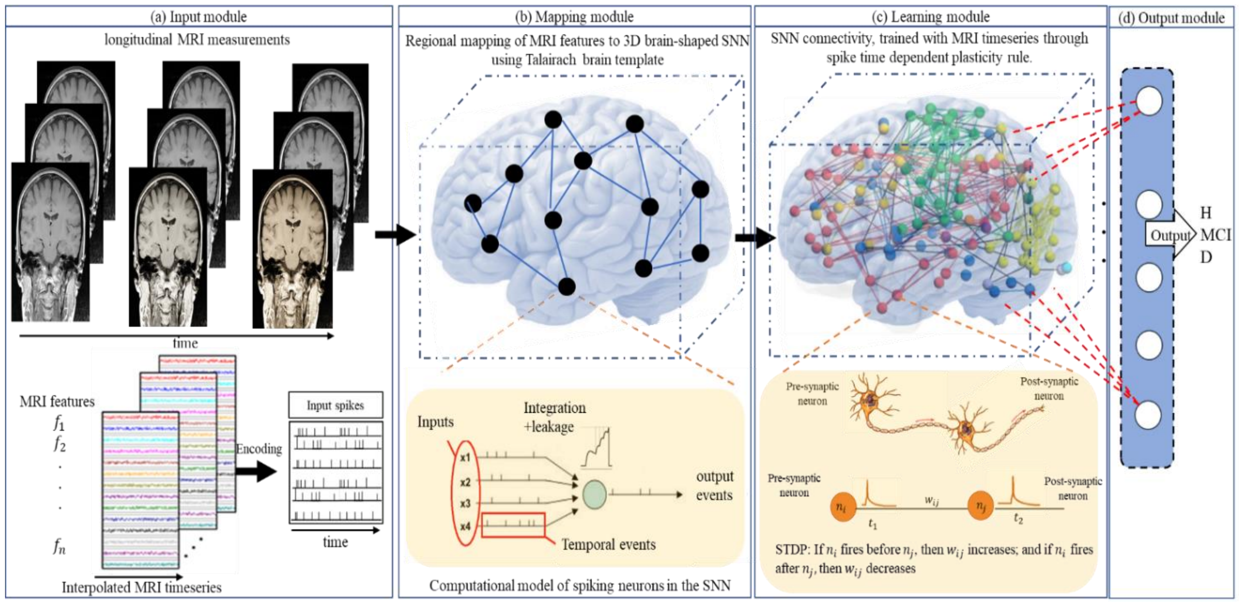


(d) Neuron proportion based on spike transmission

- SNN achieve better accuracy
- SNN predict stroke much earlier than other methods
- New information found about the predictive relationship of variables

Personalised prediction of dementia using longitudinal MRI data and NeuCube

M. Doborjeh, Z.Doborjeh, A.Merkin, H.Bahrami, A.Sumich, R.Krishnamurthi, O. Medvedev, M.Crook-Rumsey, C. Morgan, I.Kirk, P.Sachdev, H. Brodaty, K. Kang, W.Wen, V. Feigin, N. Kasabov, Personalised Predictive Modelling with Spiking Neural Networks of Longitudinal MRI Neuroimaging Cohort and the Case Study ofr Dementia, Neural Networks, vol.144, Dec.2021, 522-539, https://doi.org/10.1016/j.neunet.2021.09.013,

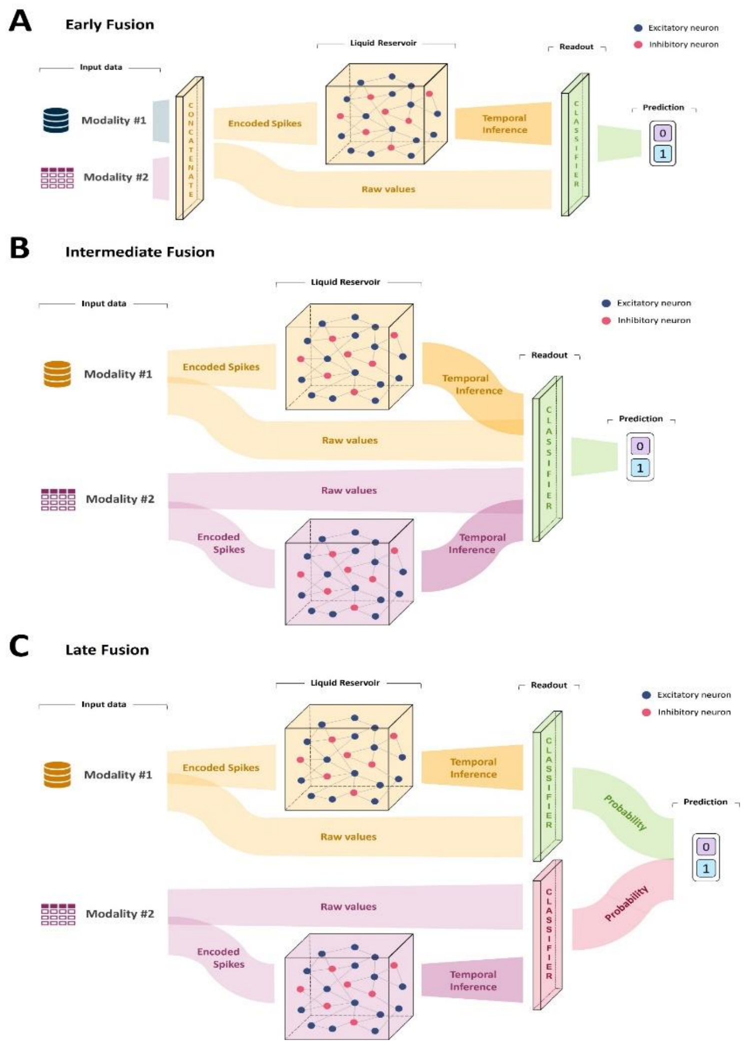


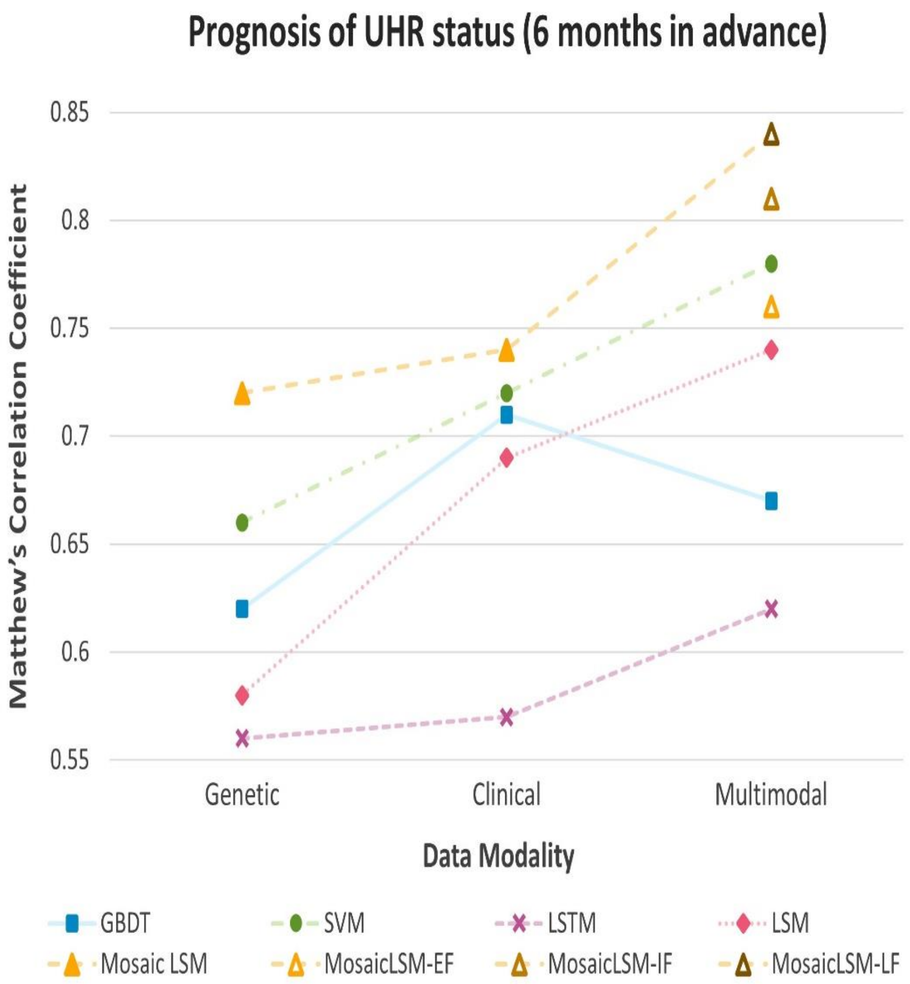
	BiLSTM Accuracy	BiLSTM F-Score	NeuCube Accuracy	NeuCube F-Score
Classification	43%	56%	95%	94%
2-year ahead prediction	40%	40%	91%	89%
4-year ahead prediction	41%	46%	73%	67%

nkasabov@aut.ac.nz

Early-, intermediate- and late longitudinal data fusion

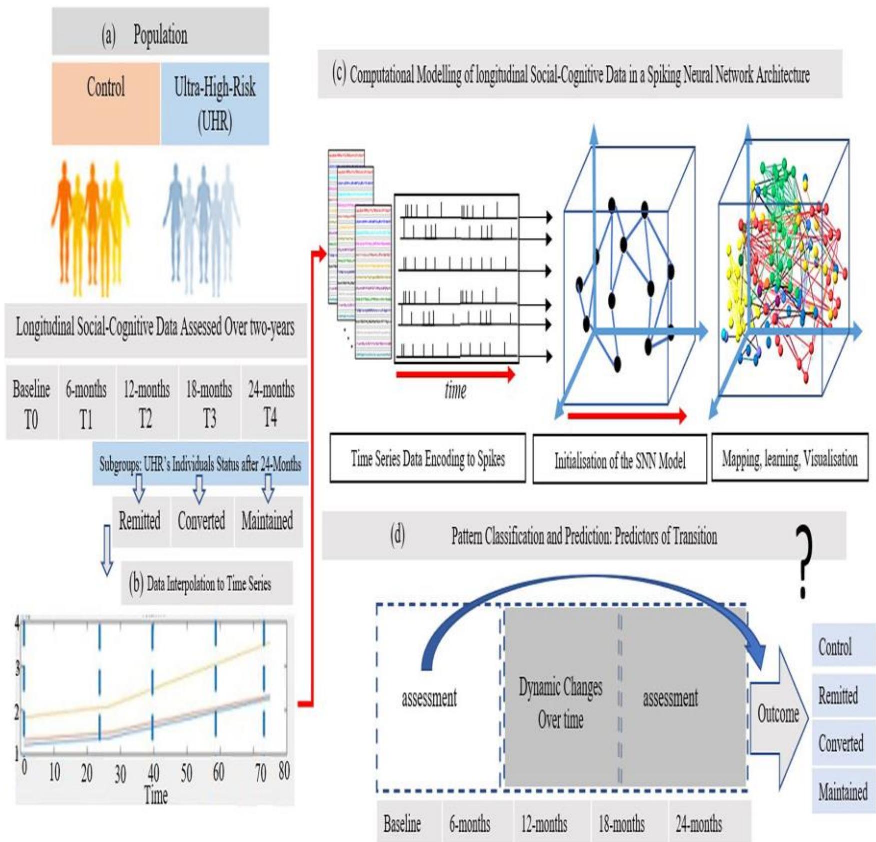
Sugam Budhraja, B.Singh, S.Tan, M.Dobrojeh, Z.Doborjeh, W.Goh, E.Lai and N.Kasabov, Mosaic LSM: A Liquid State Machine Approach for Multimodal Longitudinal Data Analysis, IJCNN 2023, paper 1570886977

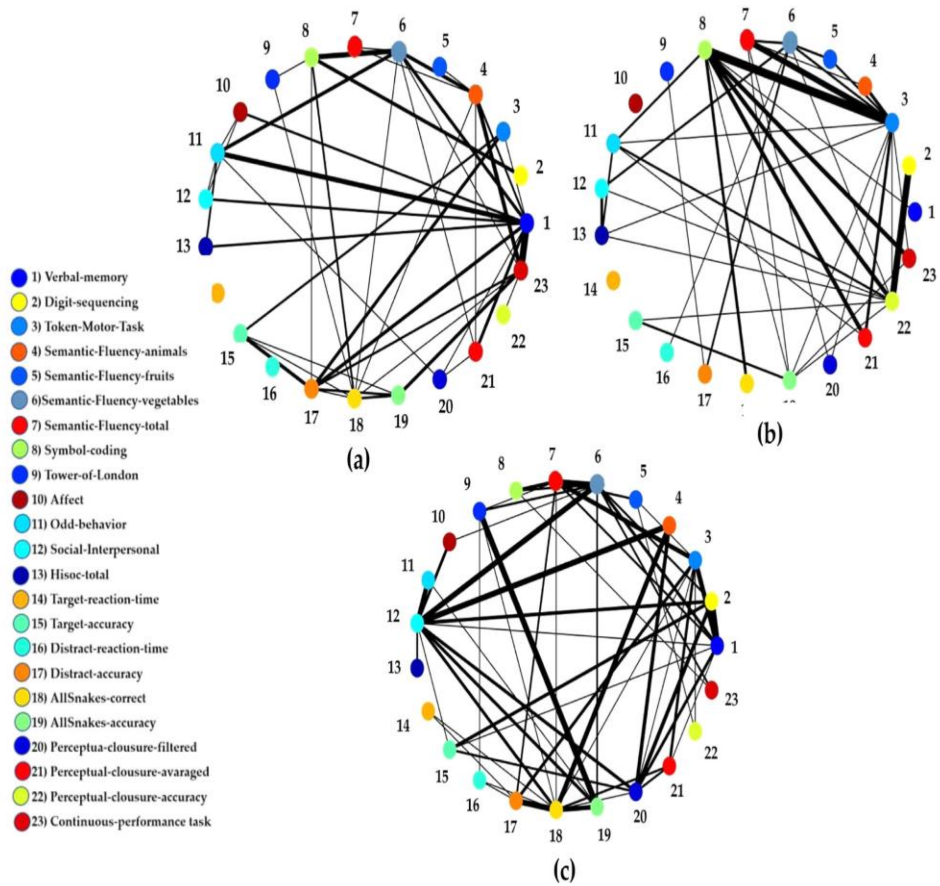




Integrating social and cognitive longitudinal data for predicting psychosis

Zohreh Doborjeh, Maryam Doborjeh, Alexander Sumich, Balkaran Singh, Alexander Merkin, Sugam Budhraja, Wilson Wen Bin Goh, Edmund Lai, Margaret Williams, Samuel Tan, Jimmy Lee, and Nikola Kasabov, Investigation of Social and Cognitive Predictors in Non-Transition Ultra-High-Risk' Individuals for Psychosis Using Spiking Neural Networks, *Schizophrenia*, 9, 10 (2023), https://doi.org/10.1038/s41537-023-00335-2



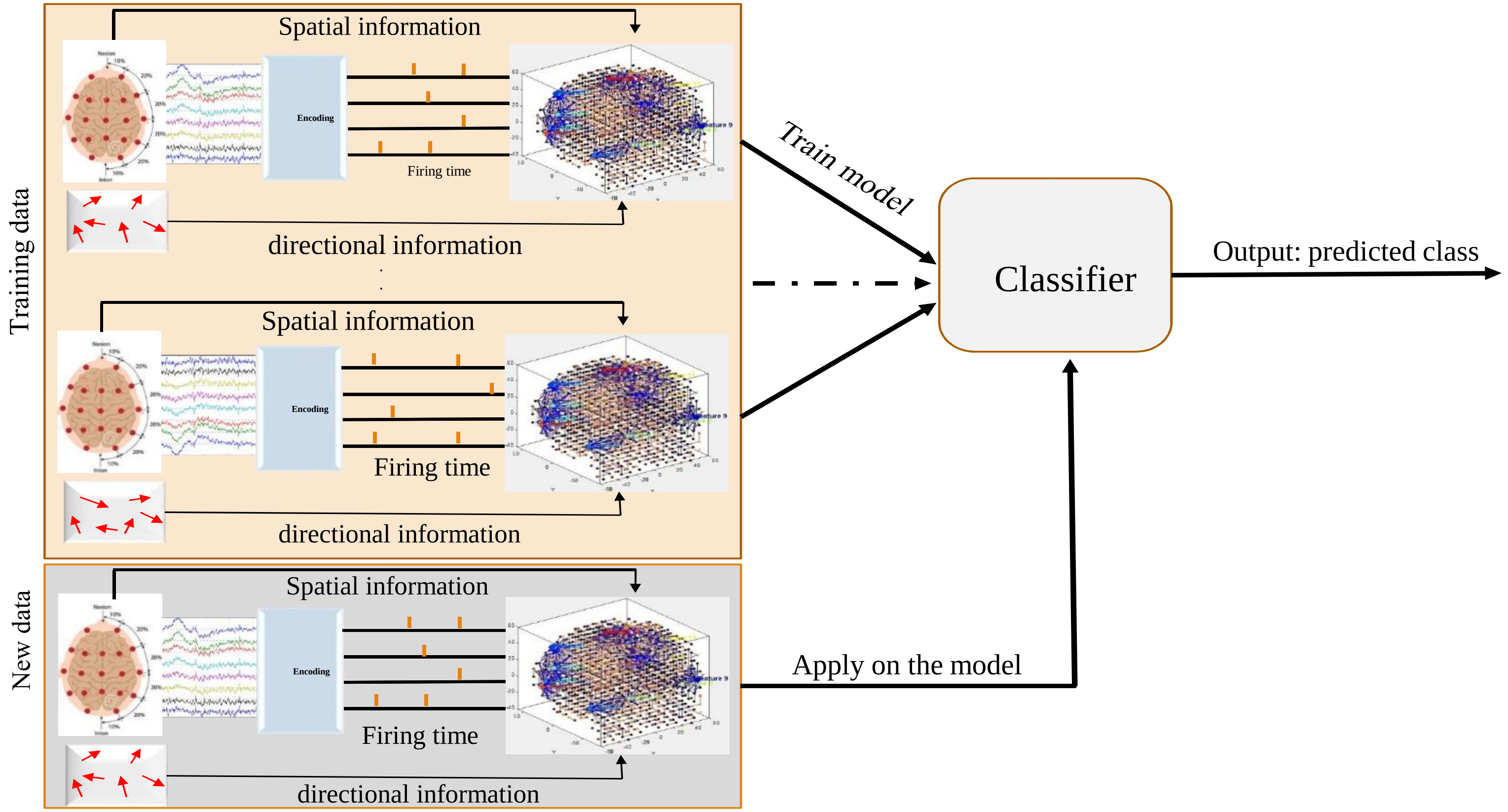


nkasabov@aut.ac.nz

Integration of fMRI and DTI data in NeuCube

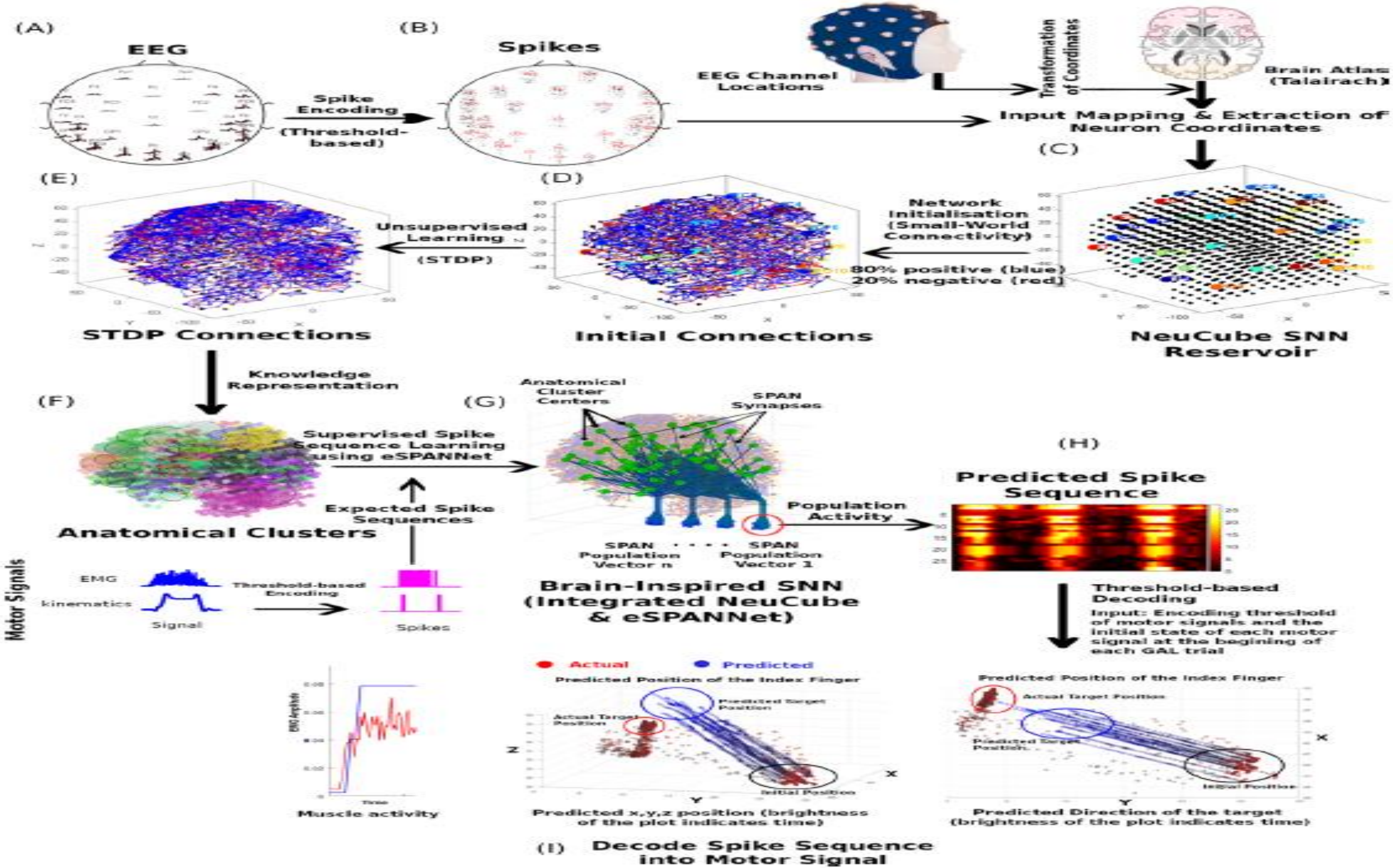
Case on response of schizophrenic patients to clozapine

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



STL for brain-body control

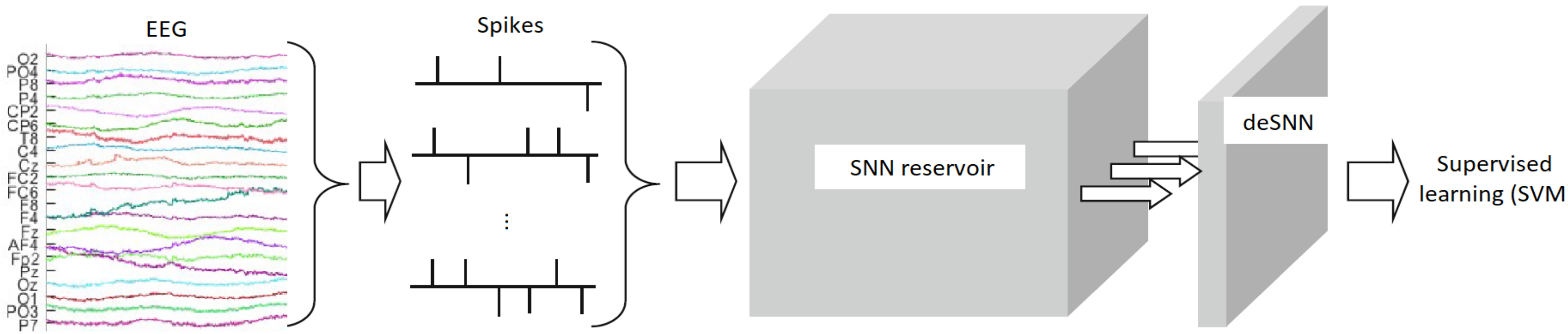
Kumarasinghe, K., Kasabov, N. & Taylor, D. Brain-inspired spiking neural networks for decoding and understanding muscle activity and kinematics from electroencephalography signals during hand movements. *Sci Rep* **11,** 2486 (2021). https://doi.org/10.1038/s41598-021-81805-4 (ranked 11 in SR in Neuroscience for 2021)

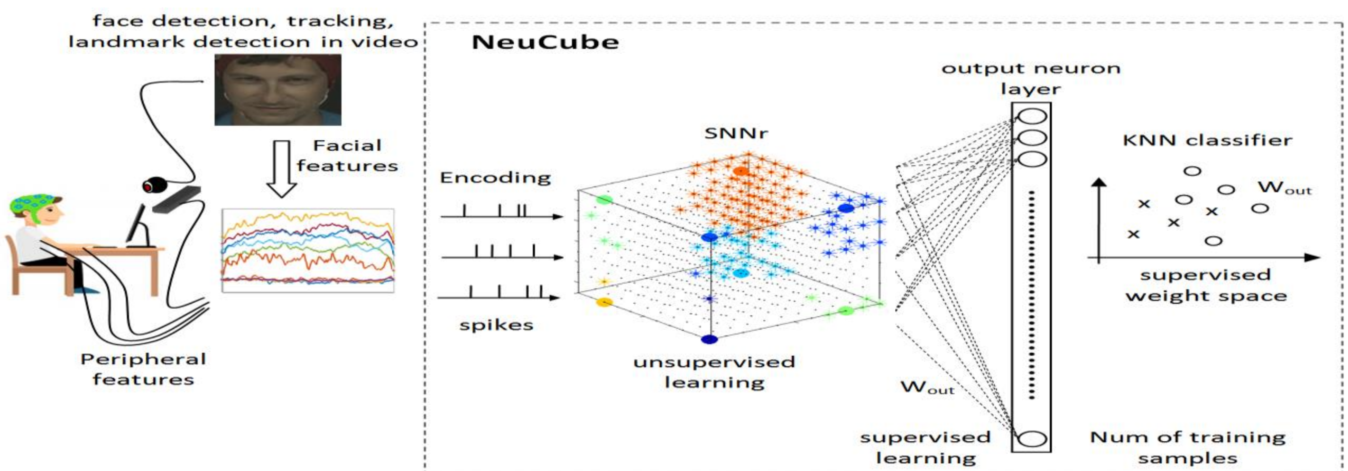


STL for affective computing with multimodal data

Wael Alzhrani, **Maryam Doborjeh**, Zohreh Doborjeh and Nikola Kasabov, Emotion Recognition and Understanding Using EEG Data in a Brain-Inspired Spiking Neural Network Architecture. *Proc. IJCNN 2021*.

C.Tan, M.Sarlija, N.Kasabov, NeuroSense: Short-Term Emotion Recognition and Understanding Based on Spiking Neural Network Modelling of Spatio-Temporal EEG Patterns, Neurocomputing, 2021.





C. Tan; G. Ceballos; N. Kasabov; N. Samaniyam, FusionSense: Emotion Classification using Feature Fusion of Multimodal Data and Deep learning in a Brain-inspired Spiking Neural Network, Sensors, MDPI, Sept. 2020

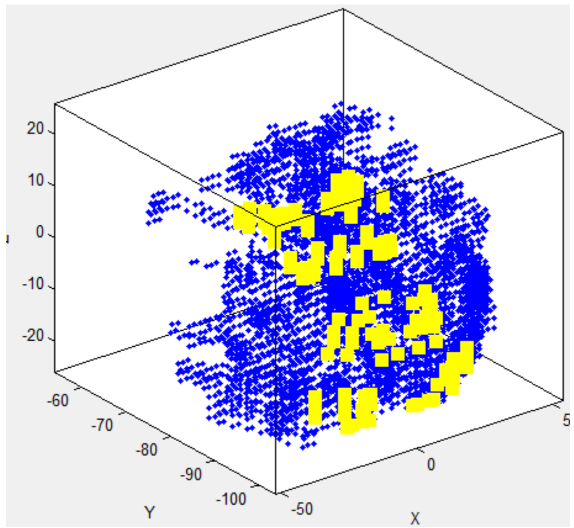
STL across subjects: hyper-scanning

B.Kelsen, A.Sumich, N.Kasabov, S.Liang, G.Wang, What has social neuroscience learned from hyperscanning studies of spoken communication? A systematic review. Neuroscience&Biobehavioural Reviews, 3 September 2020, https://doi.org/10.1016/j.neubiorev.2020.09.008;https://www.sciencedirect.com/science/article/abs/pii/S0149763420305650

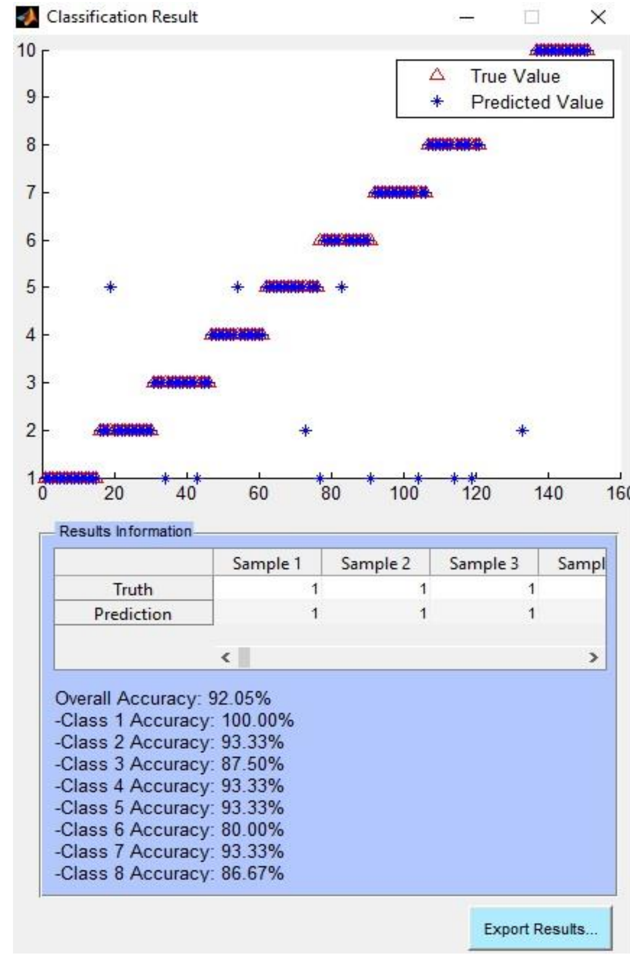
LAstolfi, J Toppi, FDe Vico Fallani, G Vecchiato, F Cincotti, C. Wilke, HYuan, D Mattia, S Salinari, B He, and F Babiloni, I, **Imaging the Social Brain by Simultaneous Hyperscanning During Subject Interaction,** EEE Intell Syst. 2011 Oct; 26 (5): 38–45.

STL of moving objects using DVS and retinotopic mapping in NeuCube

30000 moving digits in 8 fonts
and sizes from DVS MNIST



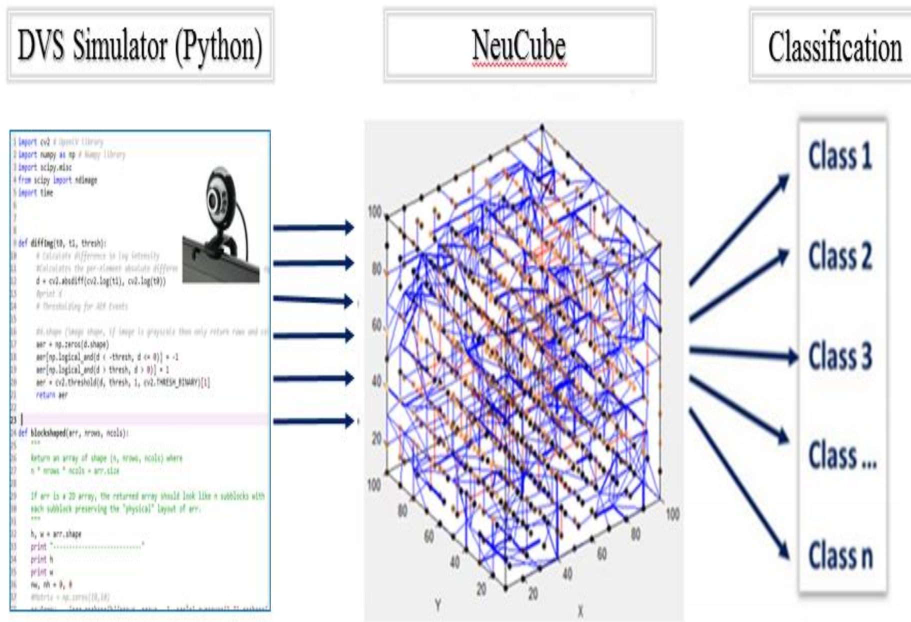
NeuCube with 4262 neurons from V1 and V2



L.Paulin, A.Abbott, N.Kasabov, A retinotopic spiking neural network system for accurate recognition of moving objects using NeuCube and dynamic vision sensors, Frontiers of Comp. Neuroscience, 2018, doi:10.3389/fncom.2018.00042.

NeuCube and DVS on mobile platforms - fast eSTL for moving object recognition

- Autonomous vehicles
- Surveillance systems
- Cybersecurity
- Military applications

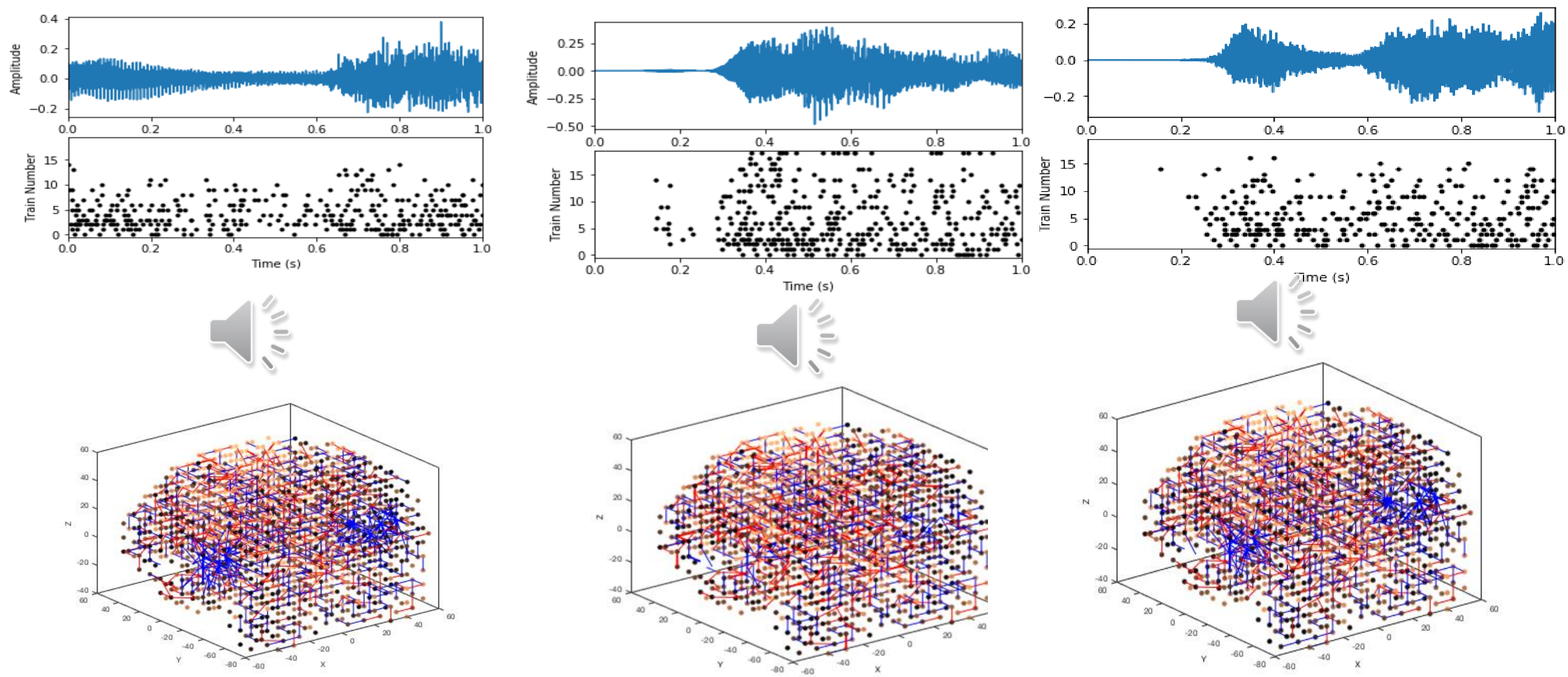


Overall Accuracy: 90.00%
-Class 1 Accuracy: 100.00%
-Class 2 Accuracy: 100.00%
-Class 3 Accuracy: 80.00%
-Class 4 Accuracy: 80.00%

nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

STL of audio-, visual and audio-visual data in BI-SNN

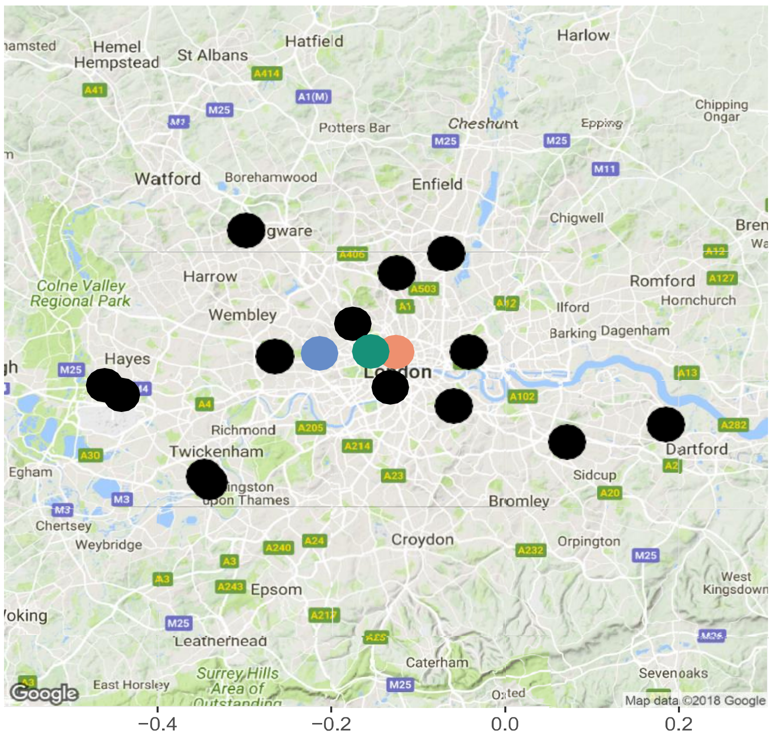
Using tonotopic, *stereo* mapping of sound and deep learning in NeuCube

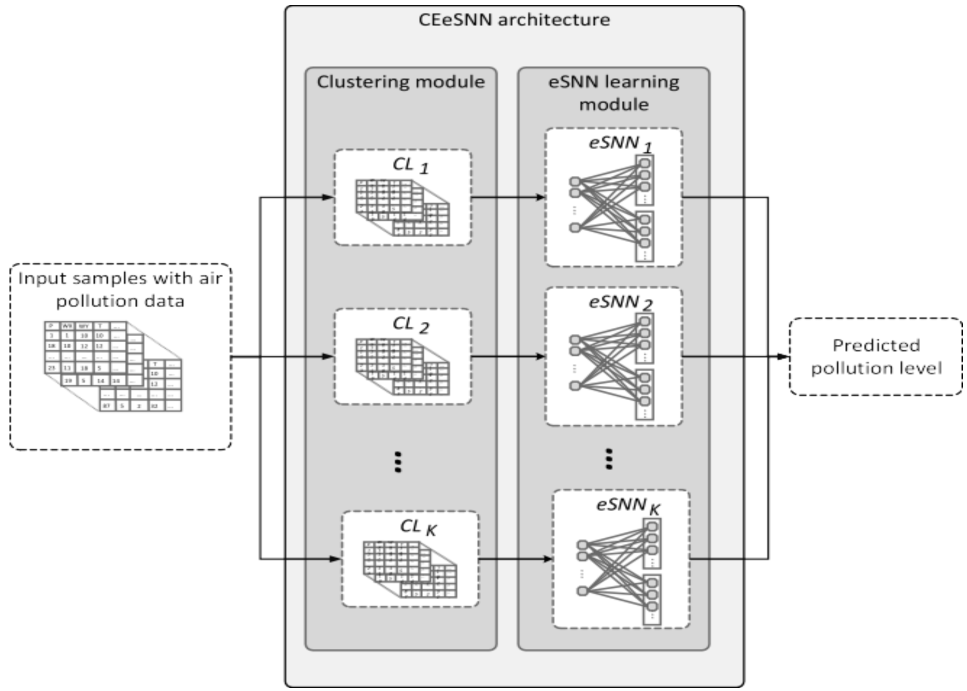


	Mozart	Bach	Vivaldi
Predicted 1	171	3	1
Predicted 2	9	176	1
Predicted 3	0	1	178

Predictive STL of streaming data from pollution sensors

Using an ensemble of eSNN for Predicting Hourly Air Pollution in London Area from sensory data





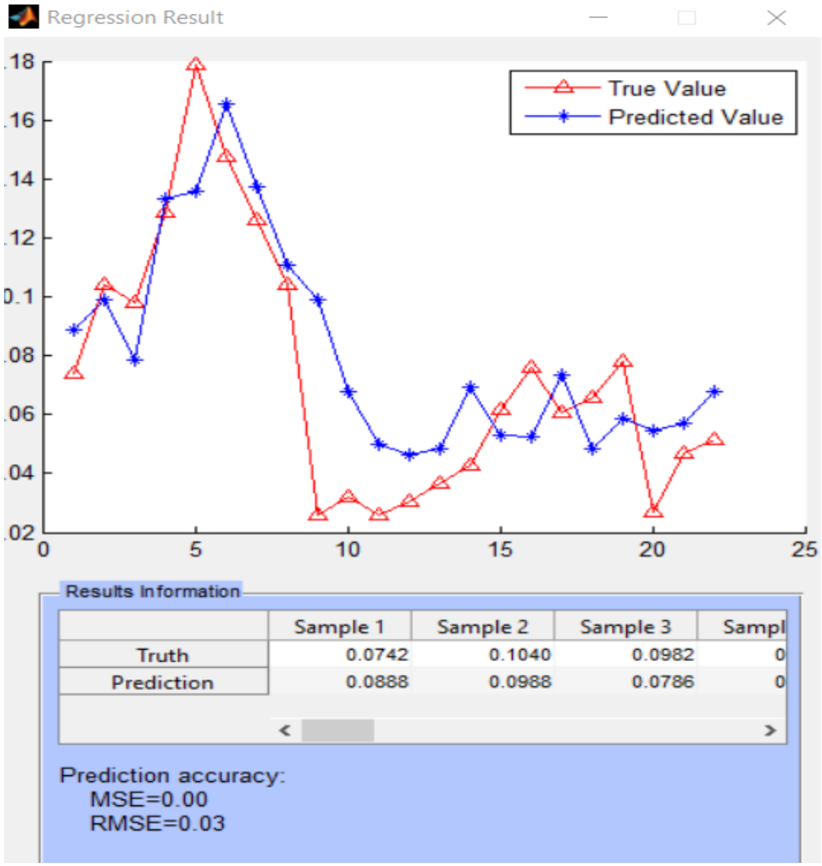
P. S. P Maciaga, N. K. Kasabov, M. Kryszkiewicza, R. Benbenik, Prediction of Hourly Air Pollution in London Area Using Evolving Spiking Neural Networks, Environmental Modelling and Software, Elsevier, vol.118, 262-280, 2019, https://www.sciencedirect.com/science/article/pii/S1364815218307448?dgcid=author

Hengyuan Liu, Guibin Lu,Yangjun Wang, Nikola 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

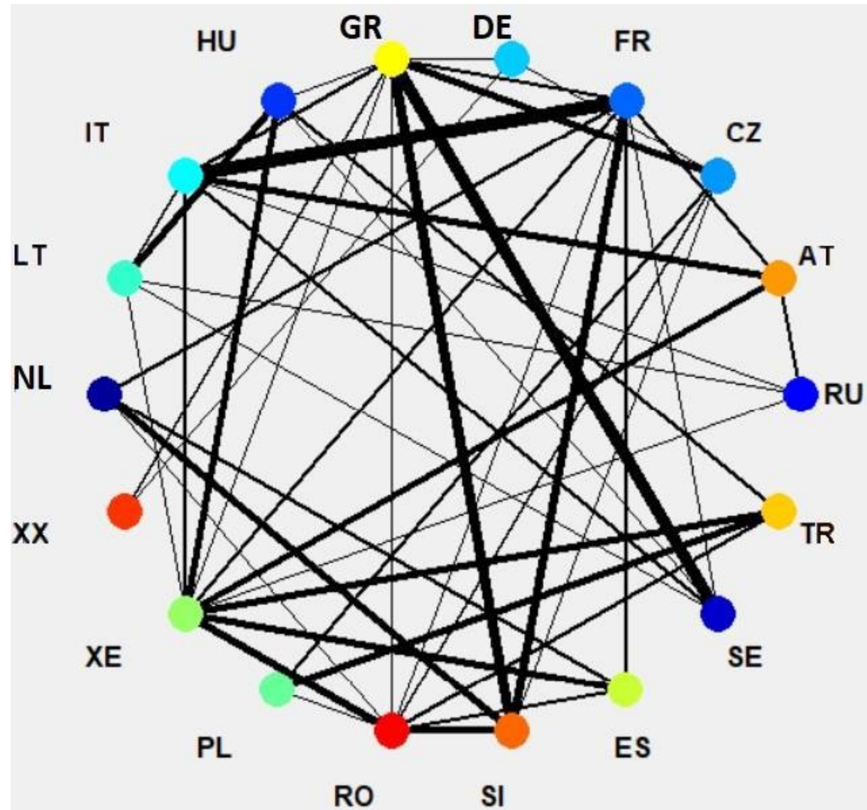
STL of financial time series data

I. Abouhassan, N. Kasabov, G. Popov and R. Trifonov, "Why Use Evolving Neuro-Fuzzy and Spiking Neural Networks for incremental and explainable learning of time series? A case study on predictive modelling of trade imports and outlier detection," *2022 IEEE 11th International Conference on Intelligent Systems (IS)*, Warsaw, Poland, 2022, pp. 1-7, doi: 10.1109/IS57118.2022.10019673.

Example: **USING NEUCUBE on a CASE STUDY ON BULGARIAN PETROLEUM OIL IMPORTS**

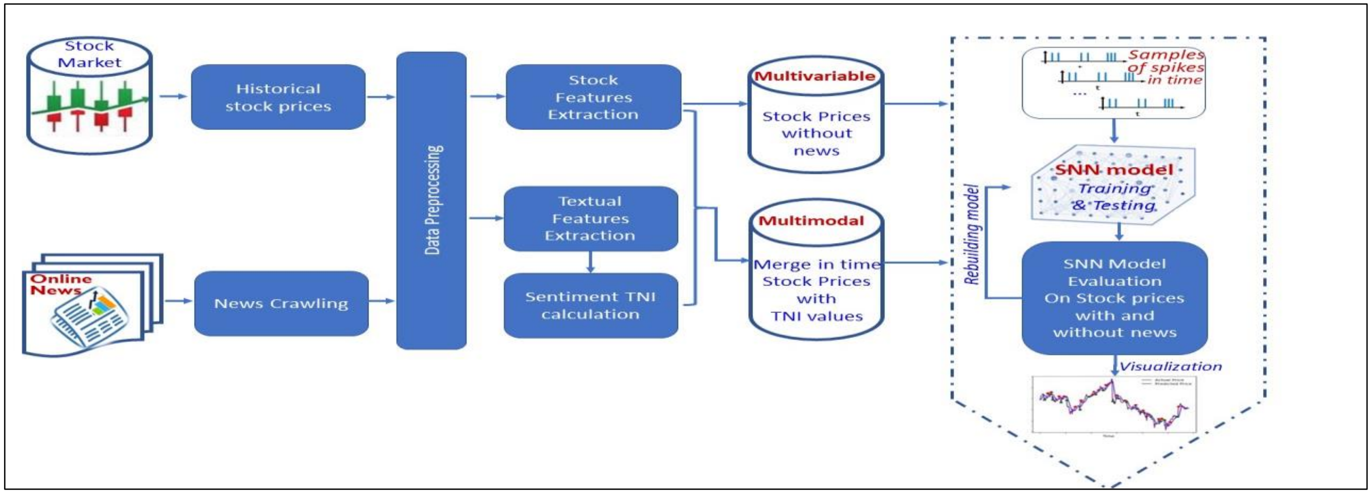


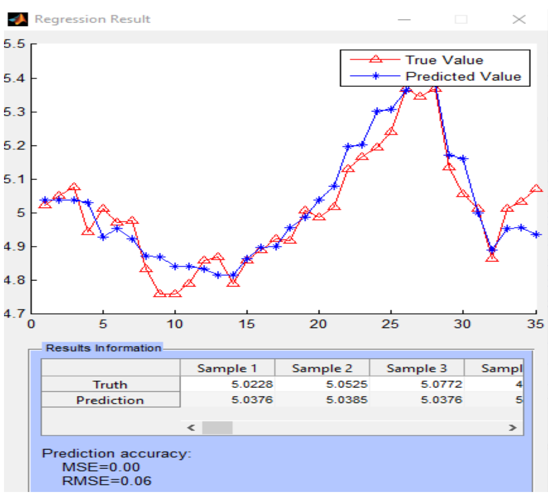
	Sample 1	Sample 2	Sample 3	Sampl
Truth	0.0742	0.1040	0.0982	0
Prediction	0.0888	0.0988	0.0786	0

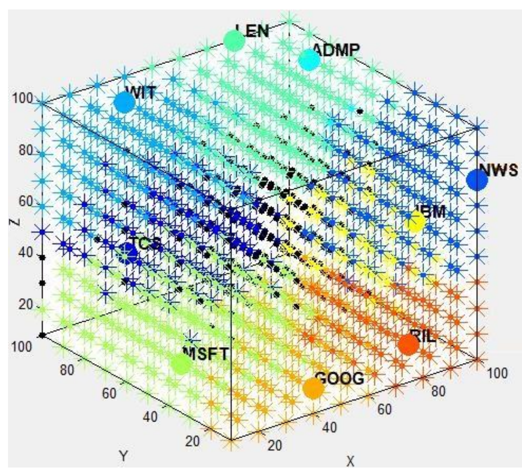


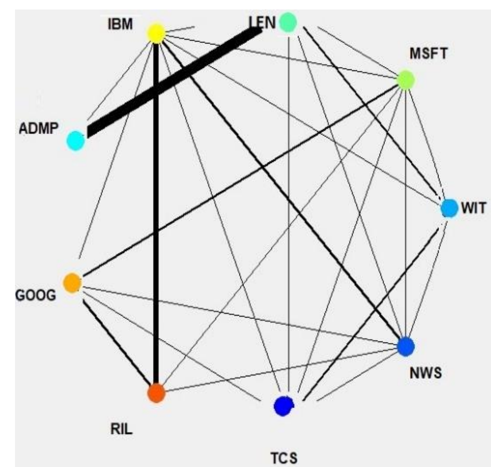
STL of multimodal streaming data: Financial data + on-line news

Nikola K. Kasabov, Iman AbouHassan, Vinayak G.M. Jagtap, Parag 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, 2023.







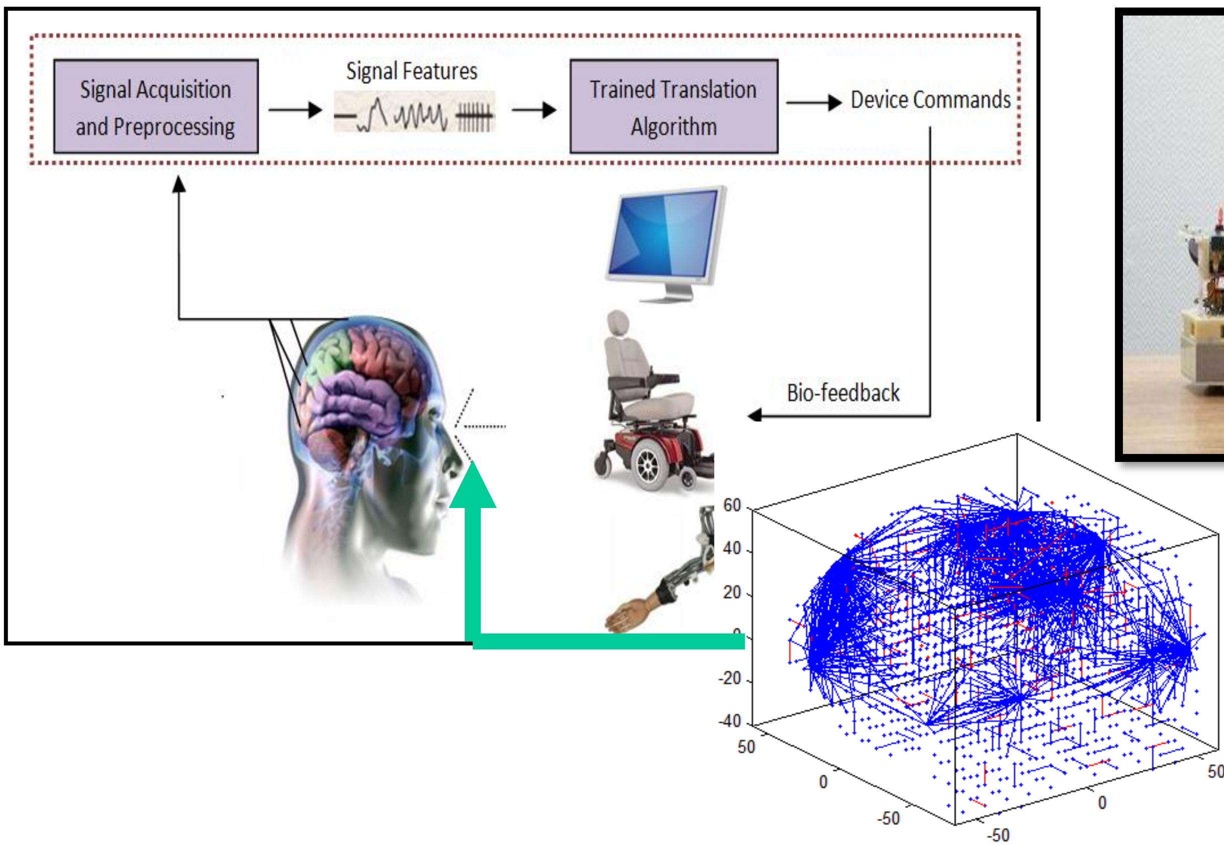


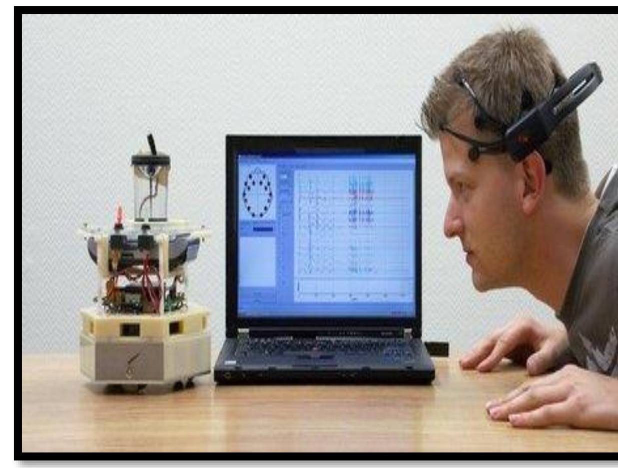
nkasabov@aut.ac.nz

6. Future directions

Brain-Computer Interfaces (BCIs) are systems trained on human brain data (e.g. EEG) for humans to communicate directly with computers or external devices through their brains

BI-BCI are designed using a brain template.

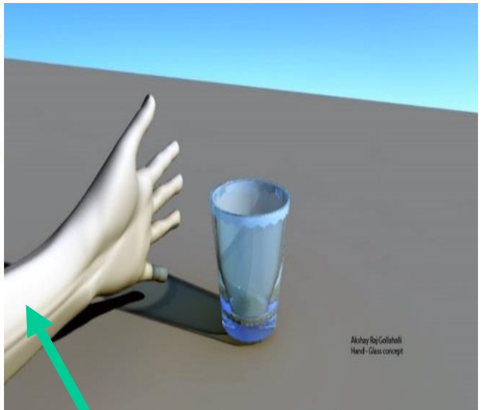


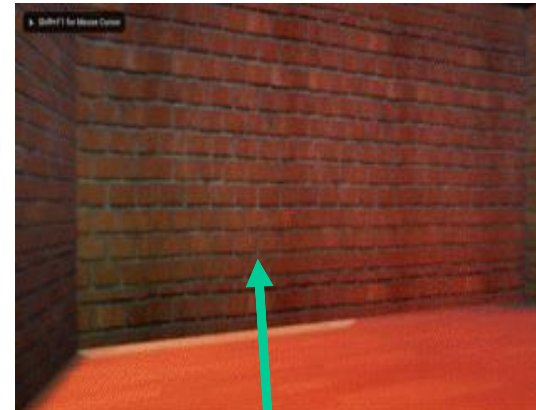


STL for modelling human- VR/AR interaction

Detecting and predicting cybersickness

Yang AHX, Kasabov NK, Cakmak YO. Prediction and Detection of Virtual Reality induced Cybersickness: A Spiking Neural Network Approach Using Spatiotemporal EEG Brain Data and Heart Rate Variability. https://doi.org/10.21203/rs.3.rs-2383481, Brain Informatics, Springer-Nature, May, 2023.

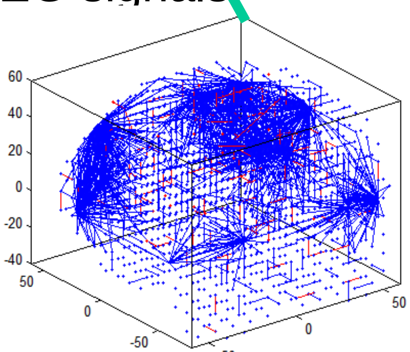


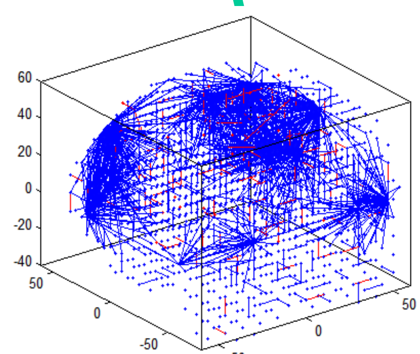


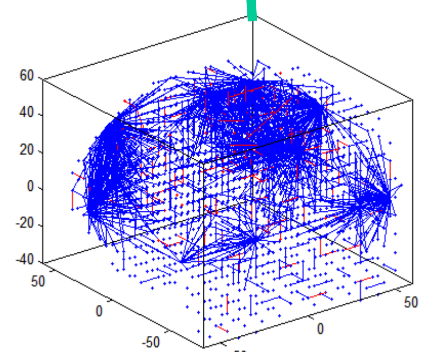
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.

A virtual environment to control a quadrotor using EEG signals.

A virtual environment (3D) using Oculus rift DK2 to move in an environment using EEG.

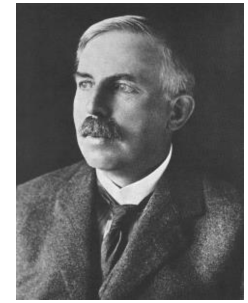






Quantum-enhanced neurocomputation: Is this the ultimate STL paradigm?

Quantum information principles: the model of the atom; superposition; entanglement, interference, parallelism (M.Planck, A.Einstein, Niels Bohr, W.Heisenberg, John von Neumann, **E. Rutherford**)



Ernest Rutherford (1871-1937)

- *Quantum bits (qu-bits)*

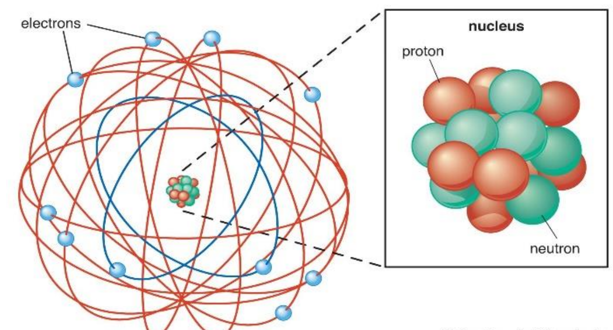
$$|\alpha|^2 + |\beta|^2 = 1 \qquad |\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

- *Quantum vectors (qu-vectors)*

$$\left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{array}\right]$$

- *Quantum gates*

$$\begin{bmatrix} \alpha_i^j(t+1) \\ \beta_i^j(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i^j(t) \\ \beta_i^j(t) \end{bmatrix}$$



- **Applications:**
  - Specific algorithms with polynomial time complexity for NP-complete problems (e.g. factorising large numbers, Shor, 1997; cryptography)
  - Search algorithms (Grover, 1996), $O(N^{1/2})$ vs O(N) complexity)
  - Quantum associative memories
  - Quantum enhanced neurocomputers:

nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

Quantum-enhanced neurocomputation architecture

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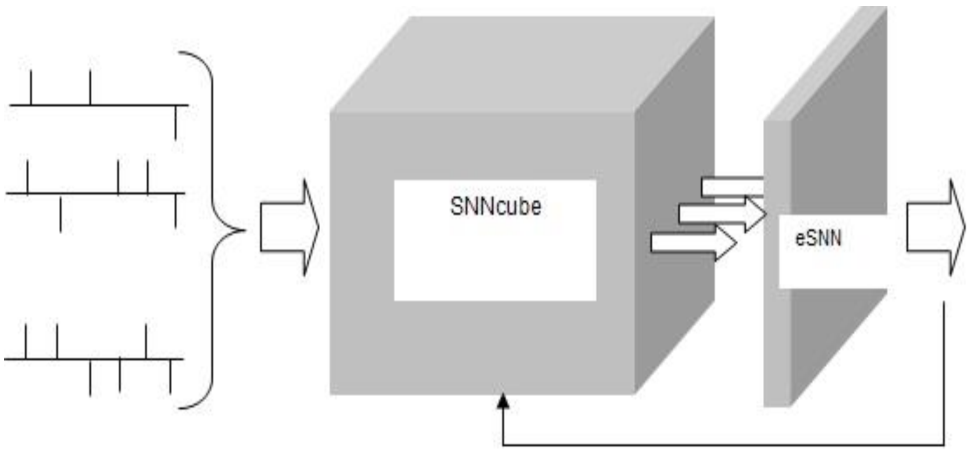

Quantum computing simulator for classification

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nkasabov@aut.ac.nz ; nk.kasabov@ulster.ac.uk https://academics.aut.ac.nz/nkasabov

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