From von Neumann Architecture and Atanasoff's ABC to Neuromorphic Computation and Kasabov's NeuCube. Part II: Applications

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Abstract Spatio/Spector-Temporal Data (SSTD) analyzing is a challenging task, as temporal features may manifest complex interactions that may also change over time. Making use of suitable models that can capture the "hidden" interactions and interrelationship among multivariate data, is vital in SSTD investigation. This chapter describes a number of prominent applications built using the Kasabov's NeuCube-based Spiking Neural Network (SNN) architecture for mapping, learning, visualization, classification/regression and better understanding and interpretation of SSTD.

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1 Introduction

NeuCube [1, 2] is the first machine learning system to analyze integrated *space* and *time* aspects of big data to deliver deeper insights. Inspired by the human brain, the most evolved learning system there is, NeuCube does the same advanced pattern recognition of complex data streams in just seconds. Much like the brain, NeuCube uses a network of virtual neurons connecting to each other or disconnecting depending on the timing of signals encoded in incoming data streams. Continuous streaming data can be fed into NeuCube which learns as it goes by constantly evolving this network of neurons. Learning is represented as chains of connected neurons that 'fire' in sequence by transmitting the incoming signal via their interconnections. Once patters in the data are represented in NeuCube as chains of 'firing' neurons, these are learned and recognized. Then new incoming data is constantly compared to the learned patterns and in this way NeuCube can predict future events as they unfold.

NeuCube consists of a set of independent mandatory and optional modules [2], some of them are:

- Module M1: Generic prototyping and testing;
- Module M2 and M3: PyNN simulator for implementation on neuromorphic hardware;
- Module M4: 3D visualization and mining;
- M5 module (I/O and information exchange) for interaction between modules.

The full configuration of the NeuCube is explained in chapter: "*From von Neumann architecture and Atanasoffs ABC to Neuromorphic Computation and Kasabov's NeuCube: Principles and Implementations*" in Springer book and it is graphically illustrated in Fig. 1.

This system is the first of its kind that can:

1. Learn and predict patterns from analyzing space and time aspects of data.
2. Use principles of the human nervous system to increase computational efficiency and reduce resource usage.
3. Facilitates understanding and rule extraction through virtual reality visualization of the model.

NeuCube has been successfully used in a number of application areas including:

- Application of NeuCube in brain data modelling;
- NeuCube and brain computer interfaces (BCI) with neurofeedback for neurorehabilitation;
- NeuCube personalized modelling in neuroinformatics and bioinformatics;
- Risk of stroke prediction;
- Predicting and understanding response to treatment in biomedical environments;
- Seismic data modelling for earthquake prediction;
- NeuCube spatiotemporal pattern recognition from satellite images in remote sensing

The above applications are briefly described in the following sections.

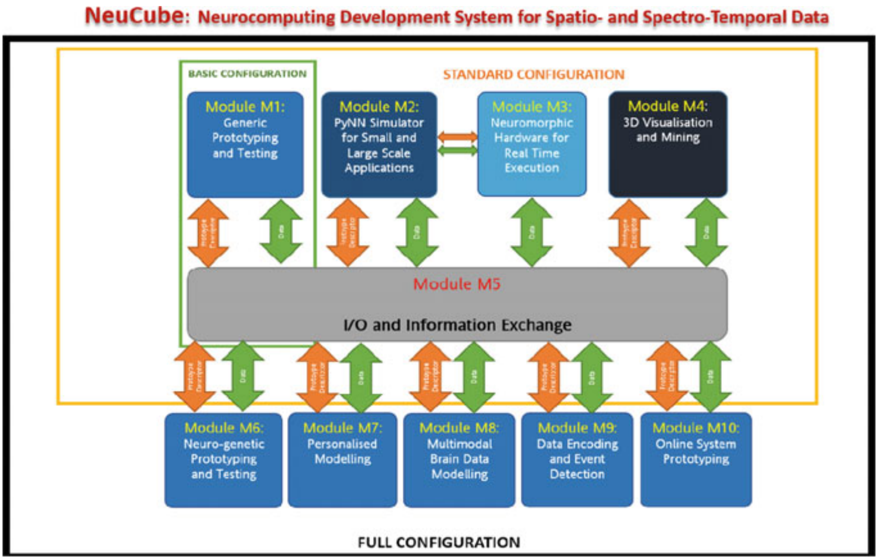
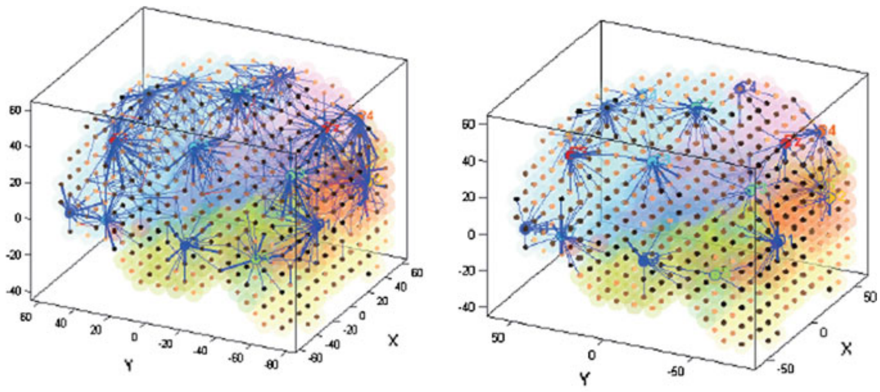


Fig. 1 The NeuCube software development architecture for SNN applications on spatio and spectrotemporal data

2 Application of NeuCube in Brain Data Modelling

NeuCube has been successfully applied to various case studies of Spatio-Temporal Brain data (STBD), the most prominent of which includes Electroencephalography (EEG) and Functional Magnitude Resonance Imaging (fMRI) data. Due to the complex spatiotemporal nature of STBD, it is often abstruse to explore the predictive potential factors using standard machine learning techniques, which are often used to examine EEG and fMRI data These techniques lack the ability to: classify neurological dynamics that occur over the time, identify the involved brain areas through meaningful brain-like visualization, and also quantify the information involved. However, NeuCube based SNN architecture is shown to be capable of such tasks and leads to better understanding of the human behavior through brain data modelling, exemplified as follows:

Progression of Alzheimer's Disease (*AD*) [3]: Motivated by the dramatic rise of neurological disorders, we proposed an SNN architecture to model EEG data collected from people affected by Alzheimer's disease (AD) and people diagnosed with mild cognitive impairment (MCI). The model developed allows for studying the AD progression and predicting whether the MCI patients are likely to be developed to AD over time. Figure 2 shows the spatiotemporal connections created in the SNN models, one is trained with the initial measurement of EEG data (time t_0) and the other model corresponds to the EEG data recorded after three months (time t1) from the same person. Referring to [3], the model enabled us to precisely visualize the



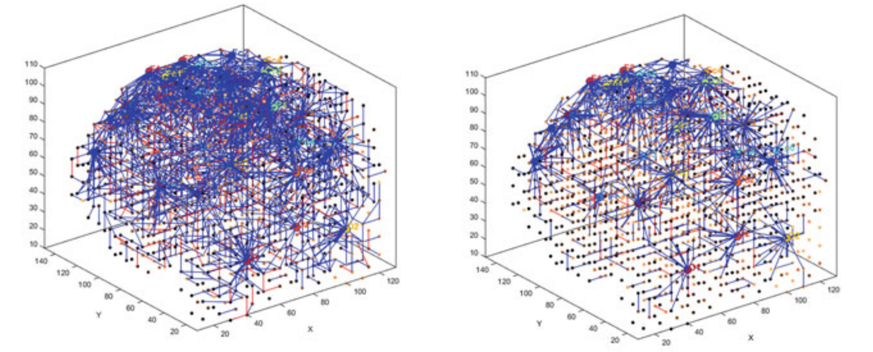
(a) EEG signal collected at t_0 (b) EEG signal collected at t_1

Fig. 2 The progression of Alzheimer disorder is captured in decrement of SNN model connectivity from t_0 to t_1. Figure from [3]

alternation of EEG band-frequencies (Alpha, Beta, theta and Delta) influenced by physiological brain ageing in AD patients.

Recognition of Attentional Bias using EEG Data [4]: Inspired by importance of the attentional bias principle in human choice behavior, we formed a NeuCube based SNN model for efficient recognition of attentional bias as influential factor in consumers' preferences. The model was tested on a case study of EEG data collected from a group of moderate drinkers when they were presented by different drink product features. Our case study findings suggest that a product brand name may not significantly impress consumers by itself. However, when the name of a brand comes along with an additional context, such as design, color, alcoholic or non-alcoholic features, etc. it may direct the consumers attention to certain features and lead the consumers to choose a product. In this particular case study, we found that attentional bias towards alcoholic-related features had more outstanding effects on the brain activity than the non-alcoholic features, as shown in the SNN connectivity in Fig. 3.

Analysis of Perception and Production of Facial Expressions [5]: This is a feasibility study of using the NeuCube SNN architecture for modelling EEG data related to a facial expression-related task. Making use of the NeuCube model allowed for the first time to discover the association between perceiving a particular facial expression and mimicking the same expression. Our finding confirms the biological principle of the Mirror Neurons System (MNS) [6] in human brain. As illustrated in Fig. 4, we identified the role of mirror neurons can be dominant in sadness emotion when compared with other emotions. Very similar areas of the brain will be activated when someone perceiving sadness emotion *versus* mimicking the same. Figure 4d shows the biggest differences between SNN models of perceiving and mimicking the sadness emotion.



(a) SNNcube connectivity based on the alcoholic feature (b) SNNcube connectivity based on the non-alcoholic feature

Fig. 3 NeuCube based SNN models trained on EEG data of alcoholic-related features in (**a**) *versus* non-alcoholic-related features in (**b**). Figure form [4]

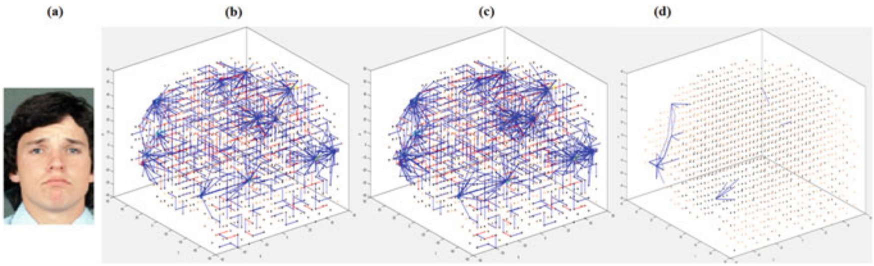


Fig. 4 **a** Exposing emotional facial expressions on a screen (sadness in this example); **b** connectivity of a SNN model trained on EEG data related to perceiving the facial expression images by a group of subjects; **c** connectivity of a SNN model trained on EEG data related to mimicking the facial expressions by a group of subjects; **d** subtraction of the SNN models from **a** and **b** to visualize, study and understand the differences between perceiving and mimicking an emotion. Figure form [5]

Predicting the Outcome of Methadone Treatment in Addict Patients [7]: We applied the NeuCube based SNN architecture to a case study of EEG data collected during a cognitive task performed by three groups of subjects: (a) untreated opiate addicts; (b) those undergoing methadone maintenance treatment (MMT) for opiate dependence; and (c) a healthy control group. The experimental results proved the following phenomena: (1) the NeuCube-based models obtained superior classification accuracy when compared with traditional machine learning methods. (2) The brain activity patterns of healthy volunteers were significantly different from people with history of opiate dependence. The differences appeared less pronounced in people undertaking MMT compared to those current opiate users. (3) The brain functional pathways of the healthy volunteers were greater and broader than either people undertaking MMT or those opiate users. (4) The STBD patterns of people on low dose of methadone appeared more comparable to healthy volunteers compared to those on high dose of methadone (as shown in Fig. 5).

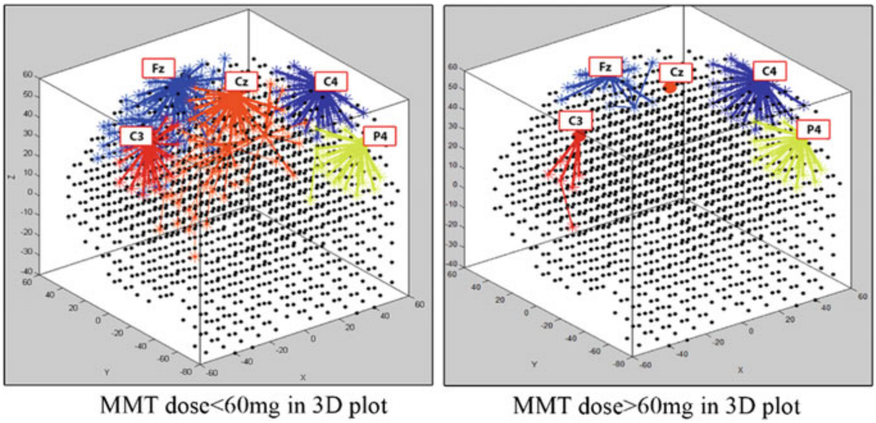


Fig. 5 The SNN models are trained on EEG data from people on low (left) and high (right) dose of methadone. Figure from [7]

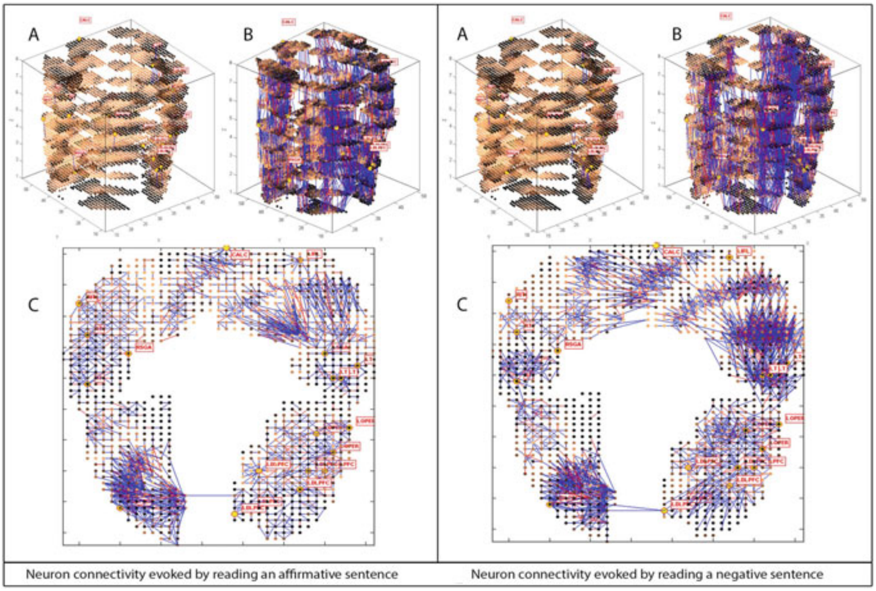


Fig. 6 The initial (A) and final (B) connectivity of a SNN model after training with two different data sets, related correspondingly to: affirmative sentence *versus* negative sentence. The final connectivity is also shown as a 2D projection (C). Positive connections are shown in blue while the negative connections are in red. Figure form [8]

Modelling and Classification of Cognitive FMRI Data [8]: We utilized the NeuCube SNN architecture for modelling the benchmark STAR/PLUS fMRI dataset [9] collected from subjects when reading affirmative versus negative sentences.

The trained connections in the SNN model (shown in Fig. 6) represent dynamic spatiotemporal interactions derived by the fMRI voxels variables over time. In this study, tracing the 3-D SNN model connectivity enabled us for the first time to capture prominent brain functional pathways evoked in language comprehension.

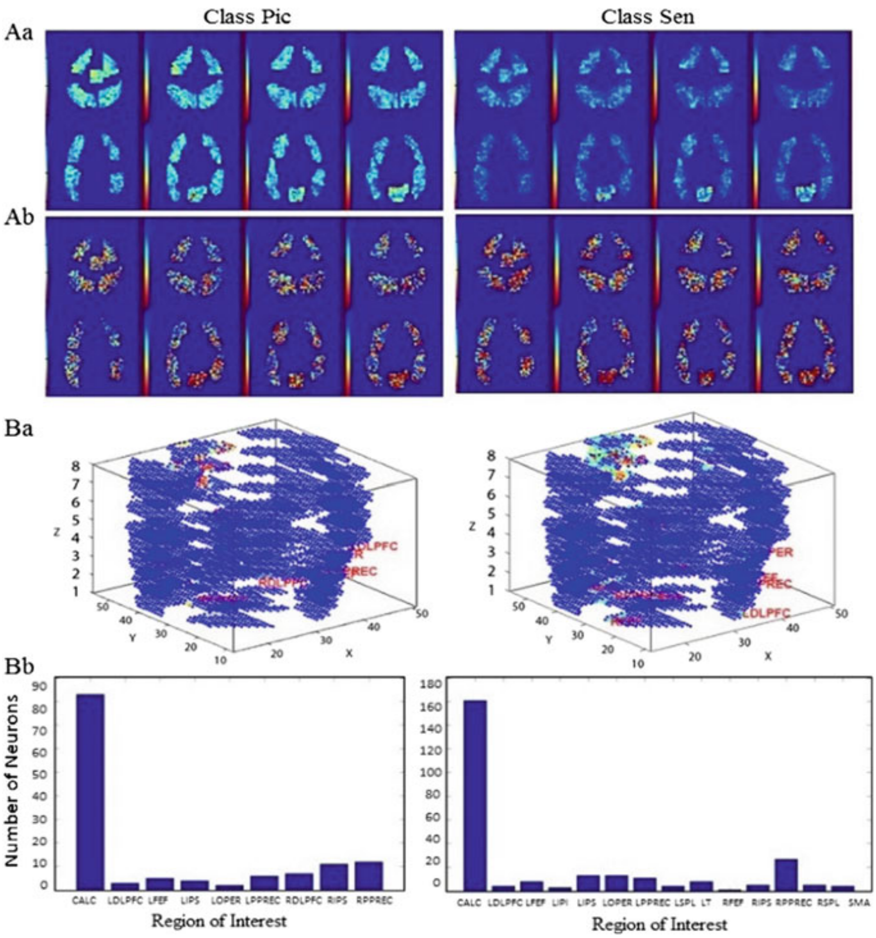


Fig. 7 Brain activation detection and brain regions mapping in the SNN model trained by fMRI data; (Aa) the 2-D SNN model activation maps for each class: watching a picture (Class Pic) or reading a sentence (Class Sen); (Ab) Probability map estimated by t-test for Class Pic (left) and Class Sen (right); (Ba) Locations of activation neurons in the averaged SNN model; (Bb) Histogram of activated neurons with respect to different regions of interest (ROIs) for each class. Figure from [10]

We found stronger spatiotemporal connections between Left Dorsolateral Prefrontal Cortex (LDLPFC) and Left Temporal (LT) while reading negated sentences than affirmative sentences. The NeuCube SNN model resulted also in a superior classification accuracy of 90% when compared with traditional AI and statistical methods.

In another research [10], we proposed a novel method based on the NeuCube SNN architecture for which the following new algorithms were introduced: fMRI data encoding into spike sequences; deep unsupervised learning of fMRI data in a 3-D SNN reservoir; classification of cognitive states; connectivity visualization and analysis for the purpose of understanding cognitive dynamics. The method was applied to the STAR/PLUS fMRI dataset of seeing a picture *versus* reading a sentence. The results are partially presented in Fig. 7 and fully explained in [10]. The evolution of neurons' activation degrees and the deep learning architecture formed in the SNN model is visualized at https://kedri.aut.ac.nz/neucube/fmri.

3 NeuCube and Brain Computer Interfaces (BCI) with Neurofeedback for Neurorehabilitation

In every 6 s, someone in the world becomes physically disabled due to a stroke. To improve the quality of life of these stroke survivors, Neurorehabilitation aims at rebuilding the affected brain motor functions through regular exercises. This intends to strengthen the remaining neural connections by utilizing the brain's ability to build new neural pathways.

Decoding movements of the same limb is an important problem in BCI for neurorehabilitation. Due to the non-invasiveness and high temporal resolution, EEG has been widely used for decoding movements in BCI. However, less spatial resolution caused by the limited number of electrodes is a challenge for pattern recognition. Previous studies on neural activities in motor-related areas of the brain during physical movements provide evidences that approximately the same areas of brain are activated during the movements of the same limb. Thus, classification of movements of same limb from EEG results in less accuracy and limits applicability of BCI for Neurorehabilitation. The state-based online classification module of the NeuCube addresses this limitation and facilitates a BCI platform for Neurorehabilitation. Using this approach we aim to detect the patient's intention to move his or her hand and pass the command to the rehabilitation robot. Figure 8 depicts a basic overview of this approach which facilitates a brain state-based classification of EEG signals using SNN.

The module encloses a Finite State Machine which acts as a finite memory to the model and a biologically plausible NeuCube SNN architecture to decode the state transitions over the time. The module follows the cue based (synchronous) BCI paradigm. While the subject is performing the task, EEG signals are recorded and

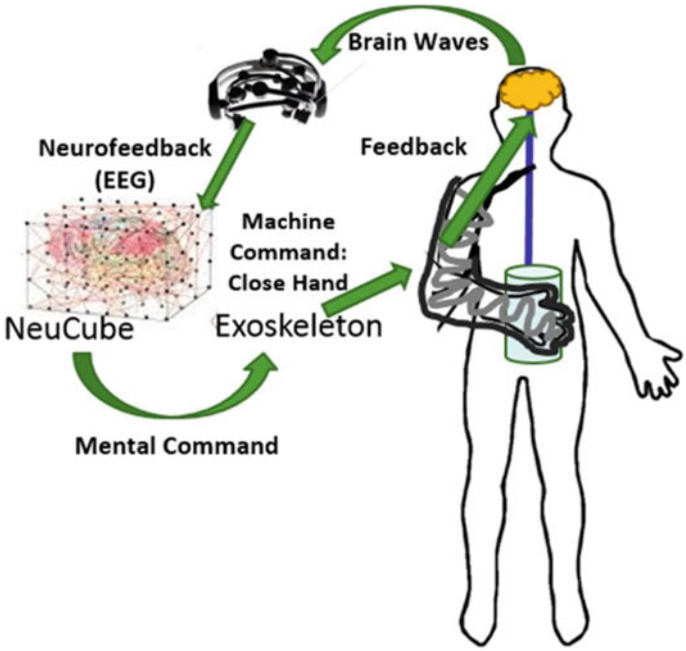


Fig. 8 Basic functional flow of BCI based neurorehabilitation through NeuCube SNN architecture

classified. This classification output is used to control the rehabilitation robots through human thoughts or intentions and also provides neurofeedback to help them to improve their brain functions.

In line with development of the NeuCube based Neurorehabilitation, two cognitive games (Grasp and NeuroRehab [11]) and one portable BCI have been developed. The concept of cognitive game does not only give a "fun" factor to the patients, but also trains them with the functionality of the product. These applications were developed for patients who have no voluntary muscular movements. The patients are trained with an imaginary task, which involves them to imagine moving a part of their body or a series of relatively complex muscle movements. A patient is equipped with EEG cap on the scalp followed by the instruction on what to imagine, so that the instructor can record the neural activity of the brain. Based on the recorded data, a NeuCube model is trained, which can be used to control objects. Once the training process is completed, the instructor performs an online classification with a new EEG data. The classified output is converted into a control signal, which controls the movements in the game.

Figure 9a is the Grasp game virtual environment, where a user is trained on how to hold a glass through EEG data using the NeuCube.

Figure 9b shows the NeuroRehab game virtual environment [11] as a two class problem, the aim of which is to move a ball either left or right depending on the

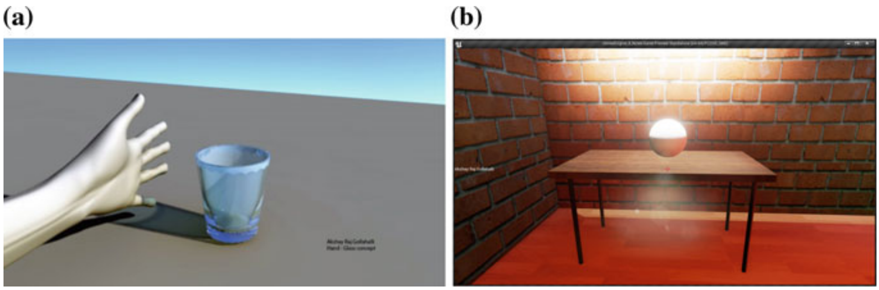


Fig. 9 **a** Grasp game virtual environment, where a user is trained on how to hold a glass using NeuCube with EEG data; **b** NeuroRehab game virtual environment, where a subject is trained to move a ball left or right. If a wrong direction is chosen, a negative mark is given. These exercises are used to help the patients to improve their cognitive abilities

thought patterns of the patient. The patient can get the overview of how the NeuCube SNN connections are being formed while he/she is trying to move an object. Our preliminary studies [12] showed that in compared to standard machine learning algorithms, NeuCube enabled us to obtain higher pattern recognition accuracy, a better adaptability to new incoming data and a better interpretation of the models.

For the purpose of making our software and hardware inter-compatible, but keeping in mind of the cost and better power consumption, we use Portable BCI's.

Portable BCI devices can be used for different application areas such as Neurorehabilitation, cognitive gaming or to control a prosthetic limb. Currently we are developing a portable BCI using the NeuCube SNN architecture to dynamically extract knowledge from brain data in real time. NeuCube being a multiplatform software, it can be easily integrated with the Raspberry Pi, which is cost effective and is widely used for prototyping software to hardware interactions.

4 NeuCube Personalized Modelling in Neuroinformatics and Bio-informatics

NeuCube advanced data analytics offers improved personal outcome prediction, personalization of treatment and understanding through identifying the most predictive factors for a person.

In Neuroinformatics, the NeuCube personalized spiking neural network (PSNN) model presents for the first time the integration of static data and dynamic STBD using SNN architecture and the approach from [13] and [14]. We hypothesize that personalized modelling with SNN could be successfully used, if the models learn from the most informative STBD samples, which are selected based on clustering of integrated static-dynamic data. In this approach, instead of building a global model and training it with STBD of the whole subject population, for every person, we will build a PSNN model to train it only on STBD of those subjects who have similar integrated factors:

- For an individual, a neighborhood of samples is collected based on similarity in integrated static-dynamic data variables.
- A model is built using NeuCube on streaming data from the neighboring samples to predict an outcome for the individual.

NeuCube based PSNN user interface is graphically shown in Fig. 10. In [15], the proposed personalized modelling approach was applied to a case study of "response to treatment" using EEG data for predicting the outcome of Methadone treatment in addicts. The PSNN models trained on a subset of informative EEG data resulted in a higher classification accuracy when compared with global SNN models. In addition, they can be used to reveal individual characteristics on brain activities that can be used to find the best patient- oriented treatment.

In bioinformatics, personalized modelling within NeuCube was successfully applied to the determination of functional dysrhythmias of the stomach, whilst preserving the spatial/temporal relationships present. The contraction of muscles that facilitate the movement required in the stomach are generated by pacemaker cells and propagated via electrical slow waves. The disruption to the normal rhythms of these waves results in various digestive disorders which include gastroparesis, unexplained nausea and vomiting, and functional dyspepsia [16], which do not have biological or bacterial causes.

Gastric slow waves are recorded using Electrogastrography (EGG) on the skin surface. This study sampled the slow waves at 100 Hz with the patient at rest, utilizing a sensor mesh of 851 nodes covering the entire stomach. In stage 1 only 4 different types of dysfunction were tested, and then expanded to 6 types in stage 2 with the inclusion of irregular irregularities. Two aspects of personalized modelling set it apart as the application of choice are the ability to model successfully with low

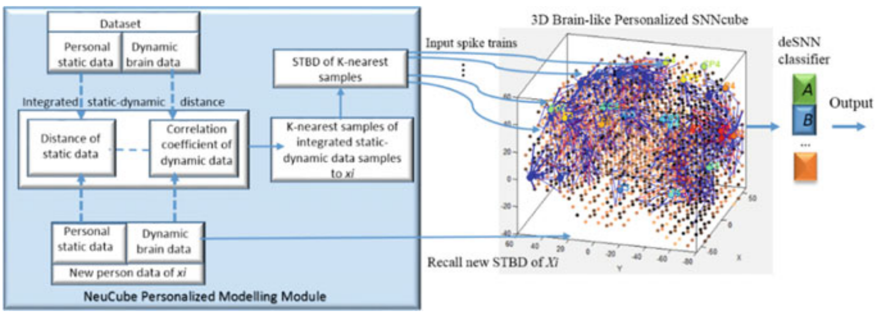


Fig. 10 A block diagram of the NeuCube based personalised modelling approach. Vector-based static data is available, each vector represents personal static clinical features. For every new input person *xi,* K-nearest samples are selected based on similarity in integrated static and dynamic STBD to sample *xi*. Then the STBD of neighbouring subjects are used to train the personalised SNN model

sample numbers, and the prediction of single samples. Couple this with the ability to specify node locations within a functional network in NeuCube, a greater degree of inherent complexity and interaction is retained by the model. In this study only 7 samples were available for each dysfunction. In stage 1 a determination accuracy of 100% was achieved for each dysfunction, but only after the introduction of a specific flexible structure within the NeuCube network. The 851 input nodes were located according to their physical locations, and a "computational" cube added to help differentiate each dysfunction. In Stage 2 various structural dimensions of the network, number of training cycles, and parameter optimization is included. On first inspection the results were surprising in that a smaller computational cube (Fig. 11a) was better along with a single training cycle. The pattern of input node activation was recorded and can be used to assist in the understanding if wave propagation throughout the system. The overall pattern of node activation was seen to be different for each dysfunction. Figure 11b shows one such pattern, for coverage of the results of stage 1 as explained in [17].

Spike encoding using the moving window method was used throughout with a threshold set to capture small changes in input signal. This allowed the distinction amongst dysfunctions especially as some dysrhythmias can occur at the same frequency as normal activity [18]. All but one dysfunction in stage 2 were predicted accurately. Reentry dysfunctions, both anterior and posterior, are known to be the most dynamic and therefore difficult to determine in conjunction with their often very close resemblance to Ectopic Pacemaker signals. This was evident in our results, along with the successful prediction of non-dysfunctional time segments.

To the best of our knowledge this study is the first to apply this type of modelling to EGG slow wave signals. It also demonstrates the diversity of the NeuCube architecture, and that irregular irregularities in signals are detectible where previously they have been notoriously difficult.

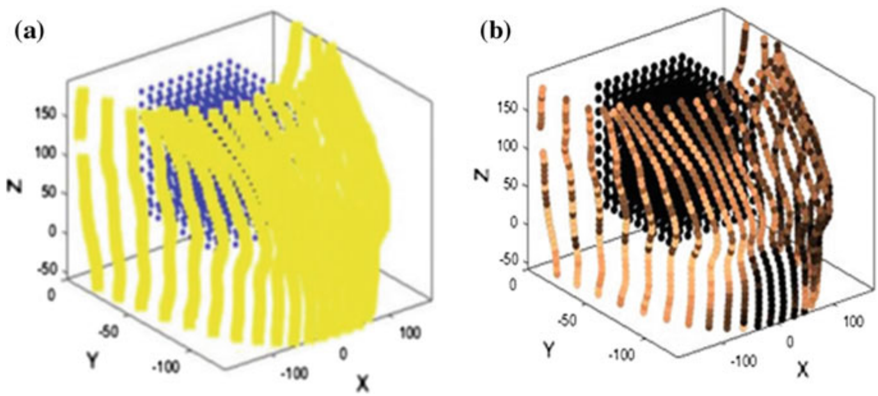


Fig. 11 **a** NeuCube node layout. Yellow nodes are input, blue are computational nodes; **b** example of average input node activation

5 Risk of Stroke Prediction

Stroke is a silent killer and a major cause of disability. About 80% of strokes can be prevented through control of modifiable risk [19, 20]. Many studies [21–23] discovered associations between environmental variables toward increment of stroke risk.

Moving toward personalized preventive measures, we applied an individualized approach during two seasons (winter and spring) based on individual's risk factors (hypertension, smoking, alcohol, diabetes, obesity and high cholesterol) through various environmental variables (weather characteristics, solar activity, air pollution) measured daily over 60 days before the stroke onset. Daily environmental data were collected through the following 12 variables: wind speed; wind chill; dry bulb temperature; wet bulb temperature; temperature max; temperature min; humidity; atmospheric pressure; sulphur dioxide (SO_2); nitrogen dioxide (NO_2); ozone (O_3); and solar radiation. Using the NeuCube-based model, we created personalized models of 46 randomly selected individuals to validate whether the combinations of inclement environment condition increase the risk of stroke occurrence in an individual with modifiable risk factors. This model also assisted to understand the relationship and interactivity exist in the combined environmental factors on individual level of risk. Finally we determined the earliest time point to best predict the risk of stroke incident for individual as preventive measures. Based on biological plausibility of association between stroke and weather/environmental characteristics, the time window between days 60 and 40 before the stroke event was used as 'low risk' days and the days in the interval between 2nd and 20th day before the event—as 'high risk' days.

Figure 12 shows the low risk and high risk deep patterns in two learned SNN models for one subject in the winter season (subject id: 9). These patterns assist us in interpreting the specific risk triggering environmental factors for individual. For

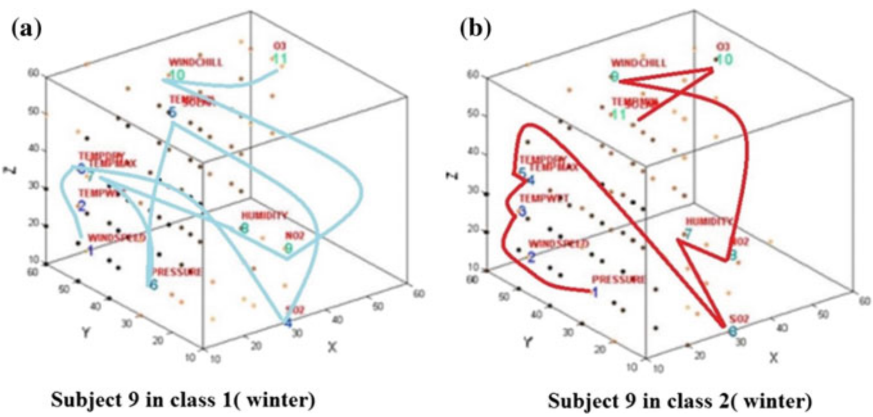


Fig. 12 Individual analysis of subject 9 for winter case study in low risk class in (**a**) and high risk class in (**b**)

example high risk can be predicted for this subject if atmospheric pressure changes first followed by wind speed, temperature wet, temperature max, temperature dry, sulfur dioxide, humidity, nitrogen dioxide, wind chill, ozone gas and temperature min sequentially.

Using the NeuCube based models for classification problem (class 1: low risk and class 2: high risk), we obtained excellent total accuracy of 95% in winter and 85% in spring for one day ahead stroke risk prediction.

6 Predicting and Understanding Response to Treatment in Biomedical Environment: A Case Study of Clozapine Monotherapy

This study was conducted as part of a large cross-sectional study investigating clozapine (CLZ) response in people with treatment-resistant schizophrenia (TRS) using EEG, MRI and genetic information. CLZ is uniquely effective for treatment-resistant schizophrenia. However, many people still suffer from residual symptoms or do not respond at all (ultra-treatment resistant schizophrenia; UTRS) to CLZ. In this study, our aim was to build a predictive model for discriminating CLZ monotherapy respondent and non-respondent individuals using multimodal brain data.

For the purpose of our investigation, we used a subset of data (resting state fMRI and DTI data with the intention of classifying subjects into groups with either TRS or UTRS. Both fMRI and DTI data for each subject were registered to a subject specific structural image and normalized to the MNI-152 2 mm atlas [24, 25].

As the fMRI data was collected during resting-state, the mean activity and deviation of activity from the voxels over time is negligible compared to task-driven fMRI data. Since a major component of our model is time dependent, we hypothesize that the discriminatory information is hidden in the voxels with significant variation in the activity over time. We selected a set of voxels with an absolute mean standard deviation of greater than 105. The final preprocessed dataset consists of one fMRI trial and one DTI trial of 2318 voxels per subject.

To create a personalized SNN model of the NeuCube, we proposed the new aiSTDP learning algorithm to train a set of 1000 computational spiking neurons, randomly scattered around the input neurons. The experimental results were reported after a grid based hyper-parameter search using the leave-one-out validation protocol. The best model achieved an overall cross validated accuracy of 72%. The area under the ROC curve for this model was 0.72. Evaluation of the confusion matrix showed equally distributed true positive/negative (UTRS: 73%, TRS: 71%) and false positive/negative (UTRS: 27%, TRS: 29%) rates.

Table 1 Comparison of classification performance by different pattern recognition methods on the binary classification task

Method	Data	Accuracy (%)	TP rate (%)	TN rate (%)
Personalized SNN + aiSTDP	fMRI + DTI	72	73	71
Personalized SNN + STDP	fMRI	56	55	57
SVM [23]	fMRI	64	64	71
AutoMLP [24]	fMRI	60	60	64.2

We have further compared the classification performance of the model built on fMRI and DTI with models built using only fMRI through a number of pattern recognition algorithms (see Table 1). For modelling fMRI data, we have used three different algorithms. The personalized SNN + STDP method uses the canonical STDP to update the weights of the SNN model in the NeuCube architecture. The other two algorithms used are the standard machine learning algorithms like SVM and MLP. The proposed personalized SNN + aiSTDP outperformed the other algorithms, not only in the overall accuracy of the model but in the true positive and true negative metrics, which allows the model to be the most robust of all. Furthermore, we have individually scrutinized the connection weights of the SNN models trained on TRS and the UTRS groups, generated by the aiSTDP learning algorithm. Figure 13 shows a comparison of the strongest mean connection weights of the TRS and the UTRS groups. The majority of the strong connections are created in the lower cerebellum and thalamus. It has been shown that by connections via the thalamus, the cerebellum innervates with motor cortical, prefrontal and parietal lobes [26]. Following cerebellar damage, neurocognitive symptoms and a cognitive affective syndrome including blunted affect and inappropriate behavior have been shown [27]. Our findings confirm the recent fMRI and PET studies that have demonstrated the involvement of cerebellum and thalamus in sensory discrimination [28], attention [29], and complex problem solving. All these functional modules are impaired in people with schizophrenia. Also a large density of strong connections is observed in the cerebellum region in the UTRS group compared to the TRS group. Similarly, larger number of strong connections are present in the thalamus region of the TRS as opposed to UTRS.

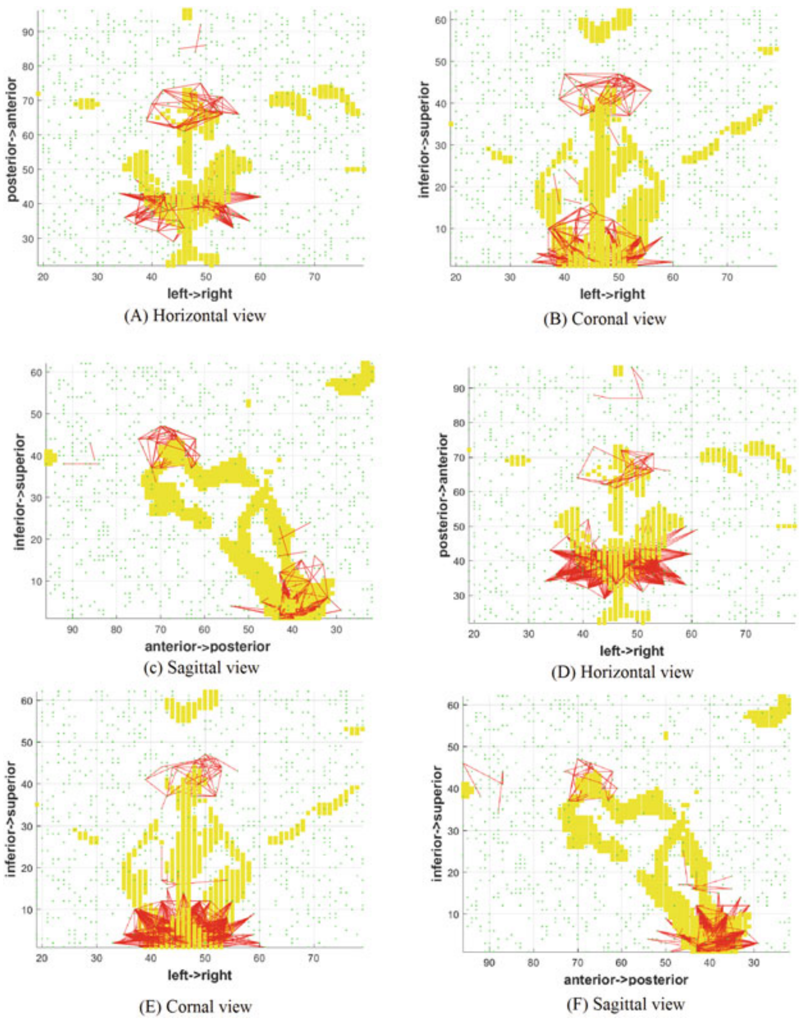


Fig. 13 Visual comparison of the strongest connections (mean weight across subjects within a group) formed in the SNN model of the TRS (the top) and the UTRS group (bottom row). The yellow colored cluster represents the input neurons and the green neurons are the computational spiking neurons

7 Seismic Data Modelling for Earthquake Prediction

Several computational intelligence approaches have extracted features from earthquake records of a particular region to predict aftershocks (smaller earthquakes happening hours to weeks after a major event), using empirical relations from geophysics such as the b-value (Gutenberg-Richter Law), Båth's Law, and Omori's Law.

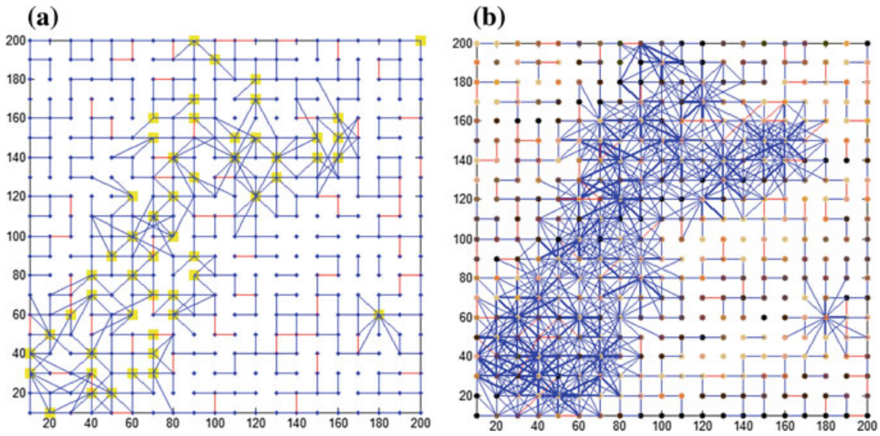


Fig. 14 **a** The SNN model is trained on a single earthquake in Christchurch area, from 5 days before and up to 1 h before the actual event; **b** the SNN model is trained on seismicity data from 52 sites across New Zealand, from 5 days before and up to 1 h before historical large earthquakes in Canterbury region The NeuCube SNN models were trained by seismicity data from 52 sites across New Zealand, from 5 days before and up to 1 h before historical large earthquakes in Canterbury (illustrated in Fig. 14). The dynamics of the SNN model learning process is visualized at https://kedri.aut.ac.nz/neucube/seismic

Recently we used multiple time-series readings of seismic activity prior to the earthquake, applying the NeuCube based SNN architecture towards earthquake prediction in New Zealand. Seismometer readings from the GeoNet web services (by GNS science, New Zealand) have been used for earlier prediction of an earthquake. We have used the NeuCube architecture to build an early prediction model and tested the prediction performance on the retrospective events in the Christchurch region of New Zealand. This region experienced major earthquake from 2010 to 2015. The NeuCube models predict severe earthquakes with remarkable accuracy, ranging from 75% at 24 h before the event, to 85% at 6 h before, and 91.36% at 1 h before.

8 NeuCube Spatio-Temporal Pattern Recognition from Satellite Images Remote Sensing

Spatio-temporal pattern recognition in remote sensing is a complex problem and the most commonly used models for dealing with temporal information. However, based on Hidden Markov Models (HMM) and traditional artificial neural networks (ANN), they have limited capacity to achieve the integration of complex and long temporal spatial/spectral components because they usually either ignore the temporal dimension or over simplify its representation.

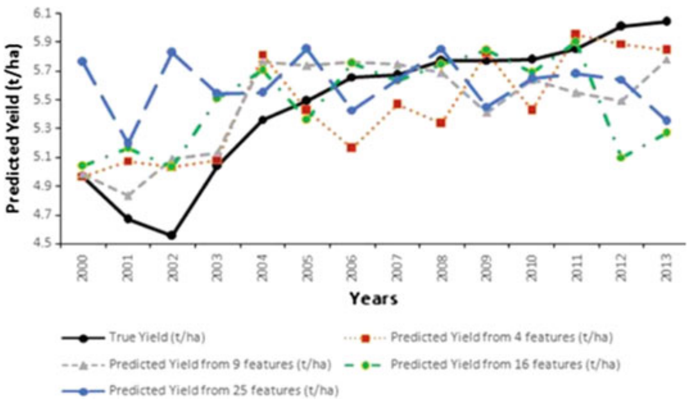


Fig. 15 Comparative analysis of the predicted yield versus the true yield for every year (2000–2013) using different numbers of features. Figure form [30]

SNN explicitly encodes temporal information by transforming input data into trains of spikes that represent time sensitive events. Our work introduced the very first SNN computational model for crop yield estimation from normalized difference vegetation index image time series. It presented the development and testing of a methodological framework which utilized the spatial accumulation of time series of Moderate Resolution Imaging Spectroradiometer 250 m resolution data and historical crop yield data to train an SNN to make timely prediction of crop yield. The research also included an analysis on the optimum number of features needed to optimize the results from our experimental data set. The proposed approach was applied to estimate the winter wheat (*Triticum aestivum L.*) yield in Shandong province, one of the main winter-wheat-growing regions of China. Our method was able to predict the yield around six weeks before harvest with a very high accuracy. Our methodology provided an average accuracy of 95.64%, with an average error of prediction of 0.236 t/ha and correlation coefficient of 0.801 based on a nine-feature model [30] (Fig. 15).

9 Conclusions

This chapter describes the feasibility study of the Kasabov's NeuCube based SNN architecture for different prominent applications of spatio/spectro temporal data. NeuCube SNN development system along with a benchmark EEG data are available at http://www.kedri.aut.ac.nz/neucube.

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