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Improved Predictive Personalized Modelling with the use of Spiking Neural Network System and a Case Study on Stroke Occurrences Data

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***Abstract*—This paper is a continuation of previous published work by the same authors on Personalized Modelling and Evolving Spiking Neural Network Reservoir architecture (PMeSNNr). The focus is on improvement of predictive modeling methods for the stroke occurrences case study utilizing an enhanced NeuCube architecture. The adaptability of the new architecture leads towards understanding feature correlations that affect the outcome of the study and extracts new knowledge from hidden patterns that reside within the associations. Through this new method, estimation of the earliest time point for stroke prediction is possible. This study also highlighted the improvement from designing a new experimental dataset compared to previous experiments. Comparative experiments were also carried out using conventional machine learning algorithms such as kNN, wkNN, SVM and MLP to prove that our approach can result in much better accuracy level.**

I. INTRODUCTION

Spatio/spectro temporal data (SSTD) is collected daily in many domains and is challenging to analyze because there are spatial and temporal connections amongst the data that need to be addressed accordingly. In them reside hidden patterns and new undiscovered knowledge that may solve numerous problems. In the health domain, the analysis of SSTD will help enhance the predictive accuracy of diseases such as stroke and heart attack and aid prevention. Classical machine learning methods have limited success in analyzing complex problems with SSTD because their capabilities are limited. This study aims to improve the on currently available methods by using new improved personalized modelling and a spiking neural network (PMeSNNr) system through the predictive modeling approach.

The main objectives of the research are understanding the effect of correlated features towards the outcome and obtaining new knowledge from hidden patterns that reside within the association between the features in SSTD. As well as from obtaining new knowledge, the research also aims to produce a model to accurately determine the earliest time point when an event (such as stroke, heart attack or earthquake) will occur in the future.

Most SSTD contains noise that may disrupt the analysis process and result in low accuracy. Classical machine learning methods removes the noise by implementing filtering methods such as the Signal to Noise Ratio (SNR). Consequently, this paper aims to demonstrate the applicability of the new system for modeling general types of SSTD and demonstrate that analyzing all data collectively without filtering the noise will be more accurate, assuming that noisy data also carries valuable information in defining meaningful associations among SSTD. Therefore a case study on stroke occurrences that contains noisy data is used to assess the feasibility of the new method. This paper also reviews the previous experimental design and methods of improving it to achieve much better accuracy at the earliest time point. This is ongoing research; since the first version of the system called NeuCube^{B} [1] was developed for modeling brain data, new architecture called NeuCubeST has been developed to model other types of SSTD. Both of these systems follow the PMeSNNr framework [2] that will be explained briefly in the next section.

II. OVERVIEW OF PMESNNR METHODOLOGY

Global modelling applied in most conventional machine learning methods has proven its effectiveness in the past, however it has a limited capability in producing models that fit each person or each case in the problem space since global modelling takes all available data in a problem space and produce a single general function [3]. The produced model is applied to a new individual regardless of their unique personal features. Common global modelling algorithms include Support Vector Machine (SVM) [4] and Multilayer Perceptron (MLP) [5]. Therefore, in the case of stroke or any medical condition, personalized modelling methods are preferred for the

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reason that they can produce a model for each individual based on their personal features. However, classical personalized modelling methods such as k-Nearest Neighbor (kNN) [6] and weighted k-Nearest Neighbor (wkNN) [7] are only suitable when classifying vector based and static types of data, not SSTD. Therefore we have extended conventional personalized modelling methods based on a Spiking Neural Network (SNN), that we believed is capable of analysing personalized temporal data more successfully than classical personalized methods.

The concept of SNN has been considered as an emerging computational technique for the analysis of spatio-temporal datasets. This is because SNN has the potential to represent and integrate different aspects of the information dimension such as time, space and has the ability to deal with large volumes of data using trains of spikes [8]. SNN models such as Spike Response Models (SRM) [9]; Leaky Integrate-and-Fire (LIF) Models [10]; Izhikevich models [11]; Evolving SNN (ESNN) [12], have been successfully utilized in several classification tasks, but they process input data streams as a sequence of static data vectors, ignoring the potential of SNN to simultaneously consider space and time dimensions in the input patterns. It can be viewed that SNN has more potential and is more suitable for SSTD pattern recognition utilizing emerging new methods such as reservoir computing [13]; Probabilistic Spiking Neuron Model [14]; Extended Evolving SNN [15]; Recurrent ESNN (reSNN) [16]; Spike Pattern Association Neuron (SPAN) [17]; Dynamic ESNN (deSNN) [18].

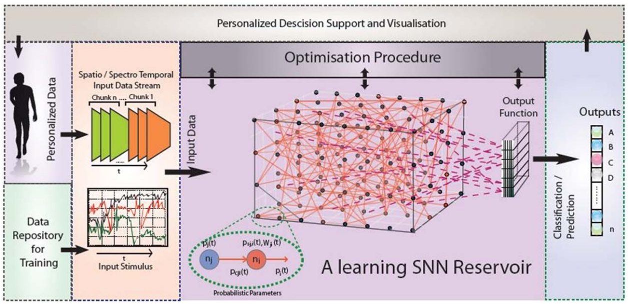

Fig. 1. Schematic diagram of PMeSNNr architecture [2]

Fig. 1 depicts the architecture of PMeSNNr. The basic components in the system consist of several functional sub-modules; a spike-time encoding module, a recurrent 3D SNN reservoir, an evolving SNN classifier and a parameter optimization module.

The spike-time encoding module will encode a continuous value of data into a train of spikes using Address Event Representation Method (AER) [19]. The method is based on calculating the difference between two consecutive values of the same input variable over time, hence is suitable when the input data is a stream and only the changes in consecutive values are processed [1]. Other encoding methods that can be implemented are Population Rank Order Coding (POC) [20] and Bens Spike Algorithm [21].

The recurrent 3D SNN reservoir will train the input spike based on the Liquid-State Machine concept, connecting leaky-integrate and fire model (LIFM) spiking neurons with recurrent connections. The reservoir comprises of a group of recurrently connected neurons. The connectivity is generally random, and the units are typically non-linear. On the whole, the activity in the reservoir is driven by the input, but is also influenced by the past. The reservoirs dynamic input-output mapping provides a crucial benefit over the simple time delay neural networks. This approach theoretically allows for real-time computation on continuous input streams in parallel [13].

The learning capability of the reservoir is through the implementation of a learning method called Spike Time Dependent Plasticity (STDP), a form of Hebbian Learning where spike time and transmission are used in order to calculate the output of a neuron [22]. Connected neurons, trained with STDP learning rule, learn consecutive temporal associations from data [1]. New connections can be generated based on activity of consecutively spiking neurons. STDP learning is considered as a viable learning mechanism for unsupervised learning of SSTD patterns.

The trained input patterns from the recurrent reservoir will then be trained again using a supervised training method such as an evolving SNN classifier to classify the class for each case. Several evolving SNN classifiers can be implemented such as evolving SNN (eSNN) [12], dynamic eSNN (deSNN) [18], Spike pattern association neurons (SPAN) [17] and many more. The parameter optimization procedure optimizes the model to find the optimal parameters that achieved maximum accuracy at earliest time of prediction.

III. Brief Description of NeuCube^{B} and NeuCubeST

In both system architectures, the mapping of data features is essential to improve the learning capability of the network and prediction accuracy. The main difference between these systems is the reservoir and mapping concept. NeuCube^{B} [1] implemented a brain structure reservoir for brain data modeling. Using NeuCube^{B}, modeling brain data from EEG readings and fMRI is a straightforward process and the connection between neurons can be interpreted through the understanding of brain regions and functions. Other types of SSTD such as stroke occurrences data, ecological data and so on, do not have these brain-like spatial connections. These types of data have their own temporal or spatial relations that are not clearly defined. Therefore the mapping of input spikes onto these input neurons is meaningless unless we understand the correlations that reside within the data.

This lead to the development of a new NeuCube architecture called NeuCubeST that is more adaptable to analyze any type of SSTD. Unlike Neucube^{B}, the NeuCubeST reservoir size is modifiable by changing the cube size values that create a recurrent 3D SNN cube reservoir consisting of LIFM neurons. Aside from a flexible reservoir size, the input neuron mapping is also flexible. The flexibility of changing the mapping of input neurons and reservoir size gives the user more control in modeling the data. Additionally, the improved functionality of automated input neuron mapping calculation helps produce the best models and saves modeling time. The automated mapping of input neuron is the key in understanding the correlations reside in the data. We believed the connections between neurons influence the learning pattern. Thus the nearer the related features are to each other, more connections are produced subsequently improved the learning process. NeuCubeST architecture does not limit the number of features to be analyzed compared to NeuCube^{B} which has only 14 input neurons.

Another crucial improvement is the way the data is visualized. Visualization of the patterns and connections between neurons are crucial in learning the SSTD. Neucube^{B} has limited visualization functionality and mapping of specific features to each input neuron is not visualized. Without this visualization understanding the correlations between features is a challenging task. Accordingly, NeuCubeST solved this problem by labeling the input neurons with the mapped features. Aside from improved reservoir visualization and mapping functionality other functionality is added to aid the modeling process, such as more types of cross validation and additional types of visualization to understand the connection between neurons.

As mentioned previously, the feasibility of these both systems were assessed using a case study on stroke occurrences. The output of the NeuCube^{B} assessment was published in [2]. Despite the fact the accuracy of the result is high, the implementation approach appears to be unsuitable for analyzing a small dataset and the knowledge gain was unclear. The case study further explained in the next section, presented a complicated problem to analyze because of the unconventional variables used in predicting a stroke event.

IV. A Case Study on Stroke Occurrences

According to World Health Organization (WHO) global report, health related problems like chronic diseases are the major cause of death in almost all countries and it is projected that 41 million people will die of a chronic disease by 2015 [24]. Chronic diseases like stroke have become a leading cause of death and adult disability in the world [25]. Although there are numerous medical and genetic risk factors associated with cardiovascular disease and stroke among such as smoking, hypertension, alcohol use, high cholesterol and obesity, that other factors such as drastic environmental changes could trigger the cause of a stroke in an individual [26]-[27]. Based on expert reviews, the influence of climate on stroke risk is biologically plausible; for example, a significant change in temperature may lead to physiological changes that increase the risk of stroke [25].

Statistical methods have been used by many researchers [26]-[31] to find association with environmental variables and stroke incidents. These are some of the studies that discovered connections between environmental changes and stroke occurrences. Studies carried out by [26], [27] and [28] revealed that a decrement in temperature, increased stroke incidence. Another study found that there is an increment in stroke incidence during cold spells and the influence of barometric pressure on hospitalizations was relatively greater than the influence of geomagnetic activity, and that the influence of temperature was greater than the influence of pressure [29]. However none of these methods investigate the combination effect of these environmental variables. We believe in order to find more meaningful associations between stroke occurrences and the external environment it is necessary to analyze them collectively.

A. Data Specification

The dataset consists of 11,453 samples (all with first-ever occurrence of stroke) from six population regions: Auckland (NZ), Perth and Melbourne (Australia), Oxfordshire (UK), Dijon (France), Norrbotten and Vasterbotten counties (Northern Sweden). These study areas are grouped into the Southern Hemisphere region (Auckland, Perth, and Melbourne) and Northern Hemisphere region (Oxfordshire, Dijon, Norrotten and Vasterbotten counties). For this study only the Auckland region with 2805 samples was selected. Patients' medical data comprise only static and categorical data that was recorded after they were hospitalized. There was no temporal recording of patient biological data until the point they had a stroke. Without the temporal medical data, predicting future stroke occurrence is difficult. Therefore, for other available temporal data such environmental data may influence stroke occurrences were utilized to construct this model.

In our previously published case study on stroke occurrences [2], the dataset consisted of 40 samples taken from the Auckland in the autumn season, only including those aged from 60 to 69, with a history of hypertension and smoking at the time of the stroke. Each sample is described by 9 features/variables (4 static patient features and 5 temporal weather features). These temporal variables are temperature (°Celsius), humidity (%), atmospheric pressure (hPA), wind speed (Knots) and wind chills (°Celsius). The weather reading of 60 days before the stroke event is collected to form the experimental data. As mentioned in our previous paper, the absence of healthy subjects, leads to the application of the case-crossover design method. Therefore, each participant acts as both 'case' and 'control' at different time intervals.

Based on previous studies [26]-[30], a decrement in temperature or inclement weather increased the risk of stroke; therefore a new dataset was extracted from the winter season in Auckland for 2002. The age group of patients is between 50 to 69 years that have a history of hypertension and are currently smokers at the time of stroke. As formerly practiced, the case over design is applied to create normal/control group from stroke patient data resulting to 20 samples altogether. In addition, a new set of temporal data are also collected including new weather variables, air pollution variables and geomagnetic activity variables. The environmental variables were measured over a 60 day period preceding the day of the stroke (excluding the day of stroke itself). The complete list contains a total of eighteen (18) features which consist of six (6) patient static features (categorical data); age, gender, history of hypertension, smoking status, season, date of stroke; along with twelve (12) environmental (temporal) features (continuous daily data) including eight (8) daily mean weather data; wind speed (Knots), wind chill (Degree), temperature dry (°Celsius), temperature wet (°Celsius), temperature max (°Celsius), temperature min (°Celsius), humidity(%), atmospheric pressure in hectopascals (hPA); three (3) daily mean air pollution data; sulfur dioxide (SO_2) ($\mu g/m^3$), nitrogen dioxide (NO_2) ($\mu g/m^3$), ozone (O_3) ($\mu g/m^3$); one (1) planetary geomagnetic activity, as measured by daily averaged Ap indices; solar radiation (Ap Index).

In order to distinguish between normal subjects (class 1) and stroke subjects (class 2), only temporal variables will be modeled and analyzed. Each class is represented by temporal data taken from two time windows of 30 days each (refer to Fig. 2). The period spanning 30 days pre-stroke occurrence until the day before the stroke event is considered as the stroke group (time window 2). We assume this as the critical time window potentially contributing to the risk of stroke. For the same subjects, the period spanning another 30 days from day 31-60 pre-stroke occurrence is taken as the normal/control group (time window 1), due to the assumption that weather parameters 60 days prior have no influence on the actual stroke event. However this appears to be an improper approach to divide the classes since the environment gradually changed overtime. Thus the exact time point when the changes in environments influence the stroke event is unclear. We suggest a transition period between normal and stroke classes, as we believe the transition period consists of ambiguous information that potentially contributes to misclassification or error.

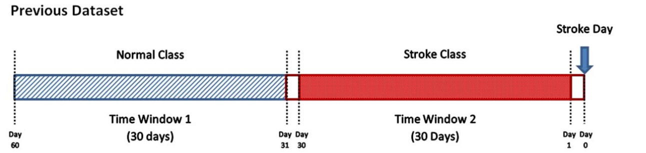

Fig. 2. Time windows to distinguish stroke and normal patients in previous dataset

Consequently, a new experimental dataset is designed by taking out the transition period from the experimental data. The transition period is between the two time windows and was decided that the time length is the same for each time window. Since the temporal environmental data that we have collected is for a 60 day time period, we consider the period spanning 20 days pre-stroke occurrence (time window 2) as 'stroke' class and the last 20 days (time window 1) as 'normal/control' class, eliminating the middle 20 days as a transition period between the time windows (refer to Fig. 3).

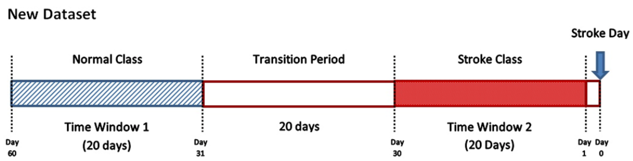

Fig. 3. Time windows to discriminate between stroke and normal patients eliminating the transition period

B. Brief Data Overview

Fig. 4 depicts the four types of temperature readings for a male subject age 51 over the period of 60 days before the stroke event. The temperature readings were temperature max, temperature min, temperature dry and temperature wet. The variable pattern between time window 1 (20 days pre-stroke event) and time window 2 shows a significant difference, where in time window 2 the temperature readings are relatively chaotic compared to time window 1 and within time window 2 the reading shows several drastic drops in temperature.

Fig. 5 depicts the atmospheric pressure reading for several patients who were 60 years old. The atmospheric pressure clearly dropping within the period of 20 days (time window 2) preceding stroke compared to the earlier 20 days (time window 1). Moreover, the readings are highly variable in that 20 day period before stroke with several drastic drops for all patients. Fig. 6 shows solar radiation readings for different patients which illustrated that the patients were exposed to high solar radiation before the stroke. The exposure to solar radiation overtime may have effects on human health. As confirmed by several researchers [32] [33], prolonged exposure could lead to skin cancer, eye disease and decrease in the efficiency of the immune system and may increase the risk of cardiovascular disease.

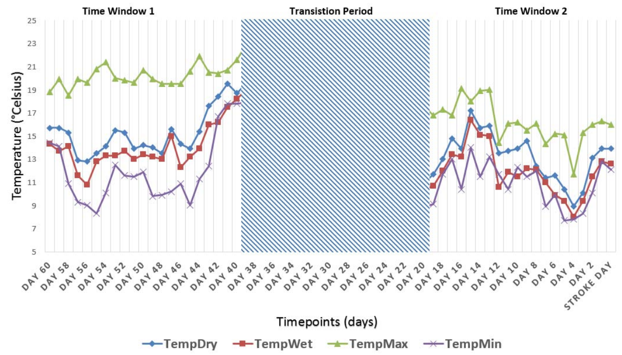

Fig. 4. Four types of temperature reading 60 days preceding stroke event for male subject, age 51

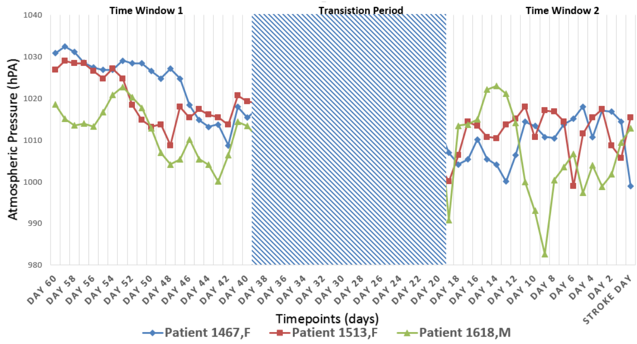

Fig. 5. Atmospheric pressure reading 60 days before the stroke event for several patients 60 years of age

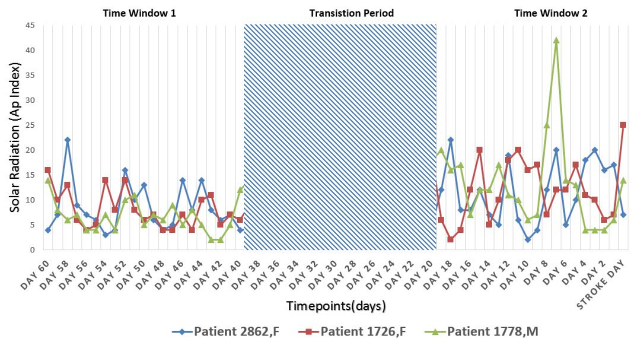

Fig. 6. Solar radiation reading 60 days preceding stroke event for three subjects

From the three types of air pollutant variables, SO_2 is illustrated in Fig. 7. SO_2 is one of highly reactive gasses known as "oxides of sulfur". These particles penetrate deeply into sensitive parts of the lungs and can cause or worsen respiratory disease, and can aggravate existing heart disease, leading to increased hospital admissions and premature death. The graphical representation of three subjects shows increased exposure to SO_2 in time window 2 compared to the exposure during time window 1. This possibly will further clarify our assumption that SO_2 in combination with other variables increases the risk of stroke.

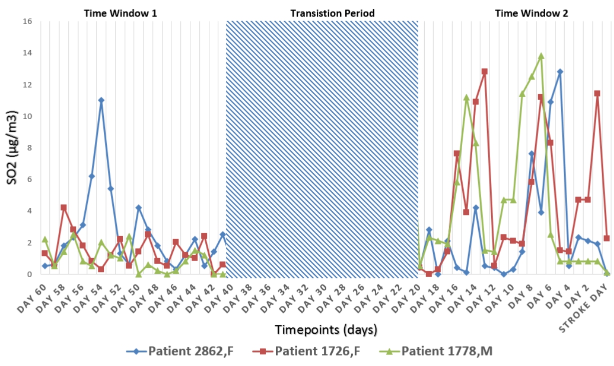

Fig. 7. SO_2 reading 60 days preceding stroke event for three subjects

V. EXPERIMENTAL SETTING

The experimental setting reported in our previous paper [2] was designed to assess the feasibility of the modelling method by generating better results compared to conventional machine learning methods. A limitation of the previous system (NeuCube^B) is that, only a random sub-sampling validation technique can be applied. Thus the previous dataset was randomly split into training and validation data. This technique is suitable if the dataset is large where an advantage of this approaches that the training/validation split is not dependent on the number of iterations (folds). However the disadvantage of this approach is that some observations may never be selected in the validation subsample, whereas others may be selected repetitively causing skewed variation of result in different random splits. In the case of stroke occurrences, the 40 samples used as training data (60%), where every 12 random samples were selected from each class; in the validation data (40%), 8 random samples were selected from each class. This is improper practice since the dataset is small and is difficult to generalize the result to an independent dataset. However, it is sufficient to assess the feasibility of the NeuCube^B architecture and encouraged us to further enhance the method by developing NeuCubeST.

A new experimental setting (refer to Fig.8) was designed to further assess the feasibility of the analysis tools as well as finding the earliest time point to best predict future stroke occurrences in an individual. These experiments are also compared with several standard machine learning algorithms such as SVM and MLP and classical personalized modeling algorithms (kNN and wkNN). The enhanced cross validation techniques in NeuCubeST enable us to carry out Leave-One-Out Cross Validation (LOOCV) for analyzing the small dataset. Through this technique the model is trained on all data except one sample and a prediction is made for that sample at the specified prediction date. Although the LOOCV technique is very expensive to compute it is a much better way to evaluate models, especially with a smaller dataset.

As depicted in Fig.8, the first experiment, takes the whole time period covering 20 days (prediction of only one day before stroke occurs). Each time period describes all features related to each time point. For example, for day 5 all the features related to day 5 will be processed as one spike pattern for that particular time point, thus preserving the temporal relationship. Whereas the second experiment looks at 75% of the whole pattern which means the prediction will be 6 days ahead. Lastly, the third experiment will take only 50% (11 days earlier) of the whole pattern to predict the stroke event. The normal class will be referred as Class 1 and stroke class as Class 2.

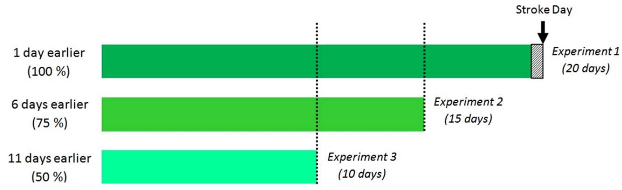

Fig. 8. Experimental design for NeuCubeST

The following parameter values were selected for optimal classification accuracy:

1) The size of the PMeSNNr reservoir is 6x6x6 making a total of 216 neurons;

2) Threshold for the AER depends on the input data as the input data is not normalized to minimize error or loss of information;

3) Small World Connectivity (SWC) used to initialize the connections in the SNN reservoir, with a radius of initial connections of 0.30. The initial connections are generated probabilistically, so that closer neurons are more likely to be connected;

4) Threshold of the LIFM neurons in the SNN reservoir is 0.5;

5) The leak parameter of the LIFM neurons is 0.002;

6) STDP learning rate is 0.01;

7) Number of training is 2 times;

8) Mod parameter of the deSNN classifier is 0.04 and the drift is 0.25.

Since conventional methods are limited to classifying static and vector-based data, the data was arranged in one vector for each experimental setting. The temporal variables for each sample were concatenated one after another, as shown in Fig 9. Experiment 1 will take all time points for 20 days resulting 240 temporal features for each sample. Experiment 2, takes only 75% of the time length (15 days) giving 180 temporal features for each sample; and experiment 3 takes 50% of the time length which yielding 120 temporal features for each sample.

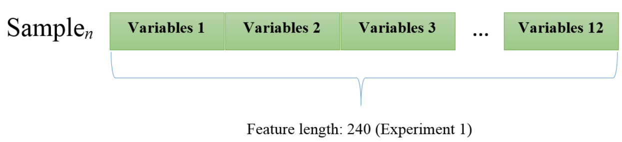

Fig. 9. Experimental design for conventional machine learning methods

All experiments are executed using LOOCV techniques without feature selection applied to the dataset. The SVM method used a Polynomial Kernel of first degree. The MLP method used 20 hidden nodes and one output, with learning rates of 0.01 and 500 iterations while kNN and wkNN used a k value of 5.

VI. RESULT

The obtained best accuracy of the NeuCubeST implementation of PMeSNNr with the parameter values described above is 95% (100% for the TP - stroke prediction, class 2; 90% for the TN – no stroke – class 1) using Leave-One Cross Validation (LOOCV). Table I lists the overall accuracy from all experiments.

The result clearly shows the PMeSNNr method is much more applicable to model such complex data, because without filtering any noise from the data the result is improved over the other conventional methods. This proves that noise also carries valuable information in defining meaningful associations among SSTD. Other conventional methods are susceptible to noise, resulting to lower accuracy if no feature selection method is applied. Furthermore, the conventional methods are clearly not suitable for analyzing complex problems that integrate different types of data because their capability is limited to learn static and vector-based data with no consideration of spatial or temporal relationships.

TABLE I. COMPARATIVE EXPERIMENTAL RESULTS FOR ALL MODELLING METHODS

Methods	Overall Accuracy (%)				
	SVM	*MLP*	*kNN*	*wkNN*	*NeuCubeST*
1 day earlier (100%)	**55** (70,40)[a]	**30** (50,10)	**40** (50,30)	**50** (70,30)	**95** (90,100)
6 days earlier (75%)	**50** (70,30)	**25** (20,30)	**40** (60,20)	**40** (60,20)	**70** (70,70)
11 days earlier (50%)	**50** (50,50)	**25** (30,20)	**45** (60,30)	**45** (60,30)	**70** (70,70)

[a] (class 1, class 2) accuracy for each class in percentage

Analyzing the result further shows that misclassification for class 1 (stroke) is very high for conventional machine learning methods. Among the conventional methods SVM performed better than the rest because of a higher correct classification for the normal class. SVM has a reputation for performing better than other global modeling methods. As for MLP, the performance is as expected since MLP is rather slow and needs many iterations for training. kNN and wkNN also did not perform well and is limited by the value of *k*.

NeuCubeST that follows the PMeSNNr architecture offers a much accurate prediction than other conventional methods. NeuCubeST with less input data still produced better and stable results. Unfortunately with less information the prediction accuracy drops. When employing the 100% time length dataset, NeuCubeST misclassified just one sample that belonged to the normal class. If we look back at the original dataset this is plausible because the original dataset consists only of stroke patients. The logical explanation here is that some of the environmental parameters somehow contain ambiguous readings at a certain time point that lead to misclassification for that particular sample. Nevertheless, prediction for stroke class is 100%, which proves our assumption about harsh environmental condition within 20 days before the stroke occurrence increases the risk of stroke. As well as our assumption that analyzing the variables collectively produces much better prediction accuracy. For the 75% and 50% time length datasets, the result is stable where both of the classes have equal classification and accuracy. This means that only using half of the input data (10 days), the system predicts that in the period of 11 days before the day of a stroke, the risk of having a stroke for an individual is 70%. Based on this prediction, individual may takes steps to reduce the risk of stroke such as protecting themselves from hazardous environmental conditions. This stroke prediction tool has the potential to enhance the capacity of existing stroke prediction by allowing more individualized risk prediction and for earlier time points than currently possible.

This study not only aimed to improve prediction accuracy, but also aimed to aid the discovery of new knowledge. Most conventional machine learning algorithms are black box methods where the learning within is not visualized. This system visualizes the learning process and through these visualization functions, relationships that reside within SSTD can be comprehended. Fig. 10 depicts the best input neuron similarity graph generated to approximately match input feature similarity graph. The spike density of the signals is calculated to produce the input feature similarity graph. Then the input neuron similarity graph is produced to show where input neurons are mapped inside the recurrent 3D reservoir.

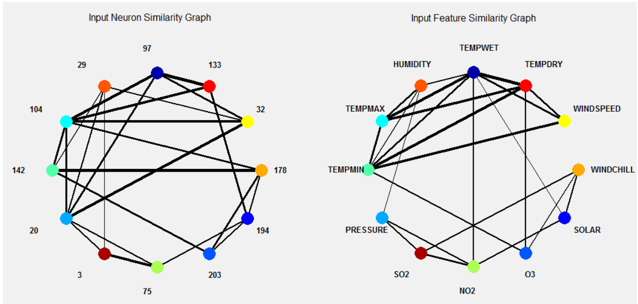

Fig. 10. Best input neuron similarity graph.

Analyzing this input feature similarity graph further, the correlations between temperature variables are very strong. So mapping these temperature variables to input neurons in close proximity is vital for better learning of the SSTD patterns. This mapping produced the highest prediction accuracy (95%), suggesting that temperature variables may have a strong influence in predicting stroke occurrences. This data was taken in winter season where temperature readings are quite low on several days, supporting most research done in the past [26]-[30] on low temperature as a trigger of stroke occurrence. In the input neuron similarity graph, we can recognize that there is a strong correlation between two air pollutant variables, SO_2 and NO_2; and a connection between NO_2 and solar radiation. One study [34] has uncovered that NO_2 gas plays an important role is solar radiation absorption under polluted conditions.

Analyzing the current problem in a smaller size reservoir produces better and stable results. The total number of neurons used to model this problem is only 216 which mean the closer the input neurons are to each other the better the learning process and the input neurons also mapped to all faces of the cube. As illustrated in Fig.11, all weather variables are mapped close to each other. Air pollution variables were mapped closely to each other with the exception of O_3 which had a stronger association with wind chill and temperature min readings.

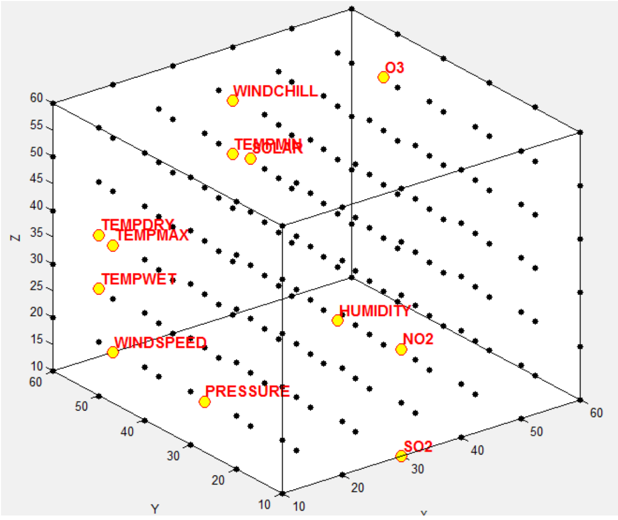

Fig. 11. Best input neuron mappings.

VII. Conclusion and Future Direction

The outcome of this study through the novel application of Personalized Modeling together with Spiking Neural Network validates its feasibility in analyzing complex problems. The evolving nature of this application and its ability to learn from new patterns or relations in SSTD enhanced the knowledge discovery process. Furthermore it can be implemented for other problems that involve SSTD such as, earthquake, volcanic eruptions and other environmental event prediction, ecological problems, contagious disease spread, cardiovascular occurrence prediction along with many other possibilities. The only drawback of this system is the expensive computation time where as it requires multiple runs to find optimal model and parameter setting. In the next stage of improvement this architecture requires a procedure to optimize the model faster. Apart from improvement to the architecture, further investigation needs to be done to understand the association revealed between variables by the modelling process. Interpreting knowledge is a very challenging task and needs to be undertaken cautiously.

As future direction, we are aiming to apply data from China using NeuCubeST for future analysis. Currently the data is being collected and will be available later this year. Using this framework on stroke case studies from other regions that have different environmental conditions such as USA and European countries to further verify its feasibility is subject to data availability.

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