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Hybrid Neural Network: A Computational Intelligent Model for Solid Waste Landfilling Suitability Mapping

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Abstract: This research introduce hybrid network (HRCFNN) for solid waste landfilling suitability mapping. It is a grouping between the recurrent neural network and cascade forward neural network. The optimum structure chosen search via several use cases. Moreover, the accomplished performance exposed that the HRCFNN has no overfitting problem. The suitability index map produced using final structure of the trained HRCFNN. The last outcomes of HRCFNN prove its robustness and the applicability of it for further application in the long-term plan developments of solid waste landfill sites.

Key words: Computational intelligent modelling, artificial neural networks, solid waste landfil suitability mapping, performance exposed, GIS

INTRODUCTION

Enormous developments have been recently recognize in Computational Intelligent Modelling (CIM) applications, mainly in classifications filed. CIM utilized in different area for instance in environmental science, water resources, agriculture and climate science (Gupta *et al*., 2015; Xu *et al*., 2013). The aim of classification is to cluster the cases or the features into categories based on their properties. For instance CIM used in landslide susceptibility mapping (Conforti *et al*., 2014) while in flood simulation to evaluate the potential flooded area into several levels of high, moderate and less probability (Kia *et al*., 2012).

ANN is one of the most widespread analytical method in CIM field. The main thing in ANN is the aartificial neuron. It is mimic the human biological cells parties as illustrated in Fig. 1. ANN were obtain a robust reputation since of its capacity to absorb the knowledge from the patterns of actual condition (Pijanowski *et al*., 2014). Generally, CIM classifications framework follows three main phases; pre-processing, training and testing the validation (Pradhan and Lee, 2010). At each phase, several processes accomplished to improve the performance of the CIM output which that can be undertaken for extra development. This study mainly aimed to introduce hybrid network (HRCFNN) with some modifications, attempts to improve the performance accuracy of solid waste suitability mapping.

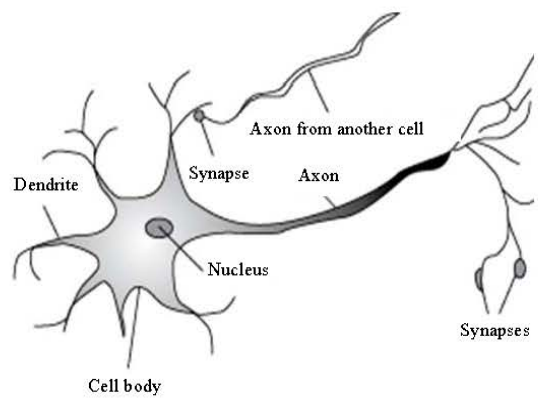

Fig. 1: Biological neuron

MATERIALS AND METHODS

Case study: The study area existing in the northwest of Malaysia. It including four states (Kedah, Perak, Perlis and Penang). It located from lat. 3°40'37.87"-6°43'22.61"N

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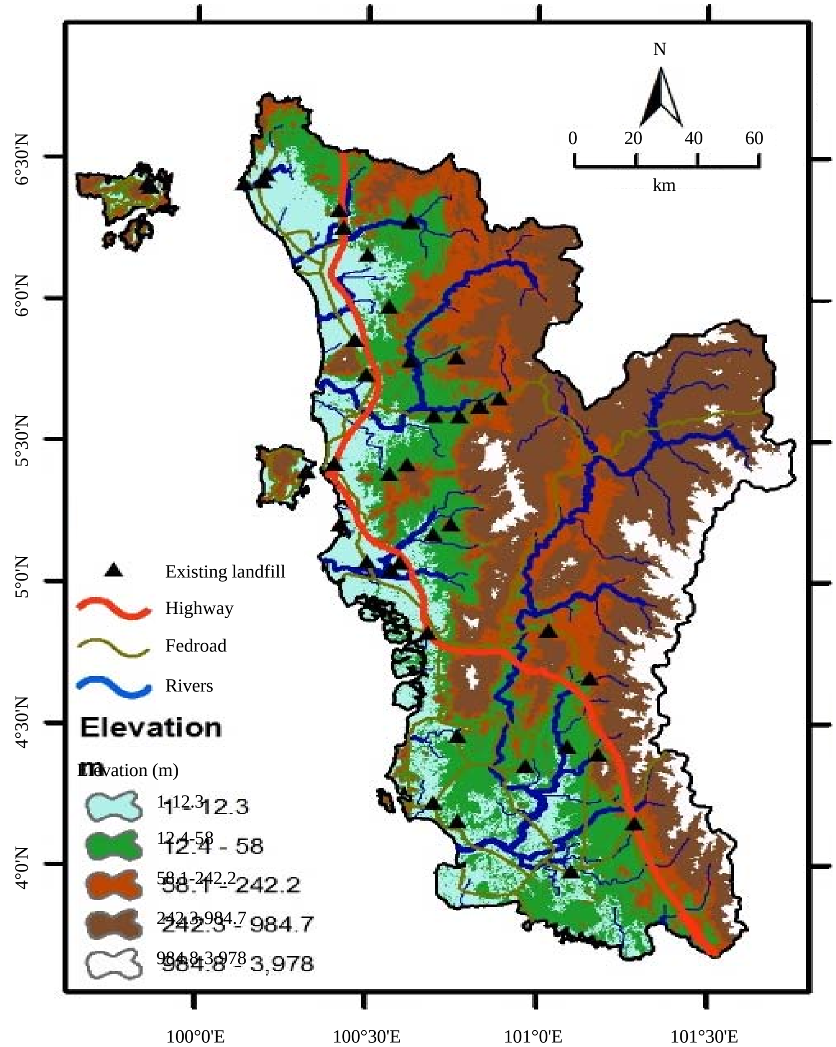

Fig. 2: Study area (Kedah, Perak, Perlis and Penang)

and long. 100°11'20.09"-101°44'41.53"E as illustrated in Fig. 2. The entire area of these states are approximately 32191 km^2 which account 9.75% of the entire Malaysia.

Hybrid HRCFNN architecture: In this study, a proposed hybrid neural network architecture named the Hybrid Recurrent Neural Network and Cascade Forward Neural Network (HRCFNN) were present. It is a hybrid between the Recurrent Neural Network (RNN) and the Cascade Forward Neural Network (CFNN). The CFNN recognized as static neural network where the signal move only in the forward direction among the hidden layers. The RNN constructed in approach permit the signals to move through two ways, forward connection and a feedback connection. The RNN considered as dynamic neural network. RNN neural networks has been extensively utilize in several implementations for instance time series and speech recognition (Jafar *et al*., 2010) while it were seldom apply in static implementations due to their very weakly performance. Intrinsically, this study introduced hybrid network (HRCFNN) through combining completely available forward connections from CFNN and backward connections from RNN in one neural network with some development. The new HRCFNN modification attempts to overreach the previous limitations and improve the performance accuracy. This architecture assist HRCFNN to re-organized and distribute the weights among the hidden layer. The introduced (HRCFNN) network anticipated be utilize to train and test the static data with respectable accuracy. Figure 3 demonstrations the architectures of the three layers for HRCFNN. It contains of three hidden layers, one input layer and one output layer with one medium layer. The HRCFNN can be demonstrate through calculating the $k^{(k)}_n$ by Eq. 1:

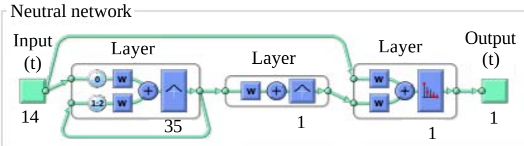

Fig. 3: Hybrid HRCFNN architecture

Fig. 4: The parallel computation for use cases

$$y_n^{(k)} = f\left(\sum_{i=1}^{M} w_{j,n}^{S} x_i^{(k)} + \sum_{i=1}^{L} w_{j,n}^{4}\, f\left(\sum_{i=1}^{L} w_{j,1}^{3}\, f\left(\begin{array}{c}\sum_{i=1}^{M} w_{j,m}^{1} x_i^{(k)} + \\ \sum_{i=1}^{L} w_{j,m}^{2}\, I\_F_i^{(k)}\end{array}\right)\right)\right) \quad (1)$$

Optimal structure of HRCFNN: An investigational effort done to finding the optimal HRCFNN structure via finding optimal training function. The capacity of HRCFNN has been tested and compared with the common twelve machine training functions: Scaled Conjugate Gradient (SCG), BFGS Quasi-Newton (BFG), Resilient Backpropagation (RP), Levenberg-Marquardt (LM), Conjugate Gradient with Powell/Beale Restarts (CGB), Fletcher-Powell Conjugate Gradient (CGF), Polak-Ribiere Conjugate Gradient (CGP), One Step Secant (OSS), Variable Learning Rate Backpropagation (GDX), Gradient Descent with Momentum backpropagation (GDM), Gradient Descent (GD), Gradient descent with adaptive learning rate backpropagation (GDA). In addition, finding the optimal HRCFNN structure require finding the suitable activation function for each layer. The ten of the major activation function were utilized: ('purelin' 'tansig' 'logsig' 'softmax' 'hardlim' 'hardlims' 'radbas' 'satlin' 'satlins' 'tribas') (Fig. 4).

Furthermore, additional parameter in ANN implementation often arises to define the number of neurons in hidden layer (Jafar *et al*., 2010). For that the experiments were perform through varied the number of hidden neurons from 1-50 and for each number of hidden neuron, the network was trained for 10 times. The epoch numbers vary from 1-1,000 to find the number of epochs that produced the best generalization for each number of hidden neuron.

Table 1: Portions and the consume time of Use cases computation

Portions	No. of neurons	Pc	Time Hours	Days
1	01-05	1	130.5	5.4
2	06-10	2	271.4	11.3
3	11-15	3	451.5	18.8
4	16-20	4	279.4	11.6
5	21-25	5	229.6	9.6
6	26-30	1	353.0	14.7
7	31-35	2	392.2	16.3
8	36-40	3	433.3	18.1
9	41-45	4	475.9	19.8
10	46-50	5	559.2	23.3

The final number of use cases of computational intelligent modelling were 60,000,000 use cases which is compute through 50 (neurons) X 12 (training function) X 10 (activation function) X 10 (number of training times) X 1,000 (epochs). The 60 m use case require massive computational time to find the best structure. According to that, this research implemented the simple concept of parallel computing to accomplish that. It have been use 5 PC's in the same time with Intel Core i5 processor with 8.0 GHz clock (Fig. 2). The algorithm were developed and implemented in Matlab environment. The search algorithm were divide to 10 portions via the number of neurons. The portions and the consume time were shown in Table 1. After the first two portions computing, some training algorithm and activation function were exclude from the search, due to the fair performance of it and to reduce the computation time.

At the end, the use case that achieve high performance accuracy were adapt and applied to training the final hybrid network. The hybrid network used spatial data set extracted from Malaysia as study area. The related required criteria identified based on the literature, including the Japan international cooperation agency guideline 2005, the united nations environment program and the national strategic plan 2005. Based on that 34 criterion were recognize. The 34 criteria represent 34 GIS layers.

Data collection separated to input and target data. The input data gathered from several resources for example; Malaysian Centre for Geospatial Data Infrastructure (MaCGDI) and NASA Website. Target data collected for the existing landfill sites through digitizing it from the satellite images in ArcGIS in order to establish the binary target map (0 and 1 where 0 = non-landfill, 1 = landfill). The ANN dataset were

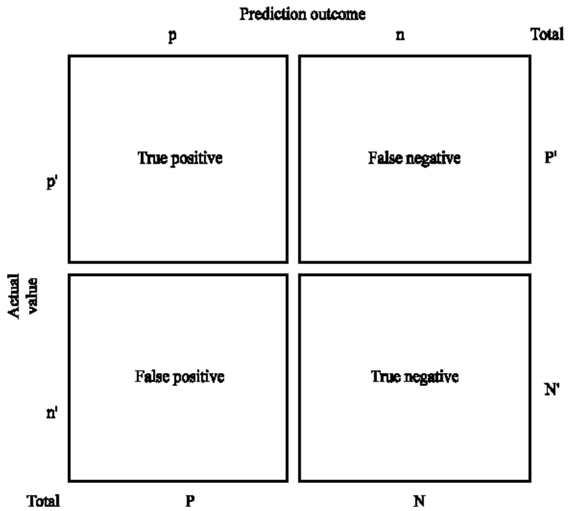

Fig. 5: Confusion matrix

extract from the GIS layer through a grid of sample points using multi values to points toolbox in ArcGIS environment. The sample point equal to 8164 point.

The dataset undertaken to several pre-processing operation to omit the noise data and improve its quality. Multicollinearity test implemented in SPSS Software to remove any redundant in the criteria. The missing samples and outliers samples were consider as noise data and removed. Then, the such as randomized and normalized (Allenmark *et al.*, 2015) by Eq. 2:

$$x_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Where:
x_{norm} = Normalized value
x_{min} = Minimum value of x_i
x_{max} = Maximum value of x_i

The final data set were contains 5902 samples with 22 criteria. These criteria are land use (environment), rivers, precipitation, humidity, soil, geology, caves, dams, faults aspect, slope, evapotranspiration, elevation, normalized difference vegetation index, land use(economic), secondary road, highway road, federal road, natural parks, local boundaries, airports and hospitals. The samples separate to two dataset 70% for training and 30% for testing, then fed to the hybrid network for ANN's modelling.

Performance evaluation: Performance evaluation of any network or model relay on how accurate the network classify the suitability maps for landfilling solid waste suitability mapping. The landfill suitability map with maximum classification accuracy is count as the maximum accurate map. The classification accuracy verified via Confusion Matrix (CM) metric as it illustrate in Fig. 5 confusion matrix (Azadi and Karimi-Jashni, 2016; Aguilera *et al.*, 2013). CM describes the hybrid network performance. The lowest value represent not accurate performance and the high value represent best performance.

Landfill suitability map: Since, the hybrid network trained and test the validation, whole study area dataset were established and fed to the hybrid network. The 87 million data samples fed to the network via 6 sections. The output vector of network were processed and used to produce landfill suitability map.

RESULTS AND DISCUSSION

The performance of HRCFNN after trained with 12 training functions with using 10 activation functions and varied number of neurons were introduced. The performance of HRCFNN network were extremely be subject to training functions and it fluctuates according to the complexity of data and network structure. The HRCFNN obtained the optimal performance is 98.26% which achieved using trainlm algorithm, trained with 35 hidden neurons. Finally, Fig. 6 exhibited that there are no overfitting among the training and testing validation accuracy.

Thus, the landfill suitability index values were compute from the trained hybrid network and the spatial datasets. The index values were ranges from 0-1 for each pixel. Figure 7 illustrates the distribution of suitability areas using 22 criteria. The stability index of new landfill sites classified to five categories of suitability for easy and visual interpretation.

The suitability map examination the number of landfill sites within each category. The high and very high categories contain 82% of landfill (37 out of 45) which support the robustness of HRCFNN. This landfill suitability map can assistance in the solid waste planning in the study area.

Thus, the landfill suitability index values were compute from the trained hybrid network and the spatial datasets. The index values were ranges from 0-1 for each pixel. Figure 8 illustrates the distribution of suitability areas using 22 criteria. While Fig. 8 illustrates only the high suitability areas. The stability index of new landfill sites classified to five categories of suitability for easy and visual interpretation. The suitability map examination the number of landfill sites within each category. The high and very high categories contain 82% of landfill

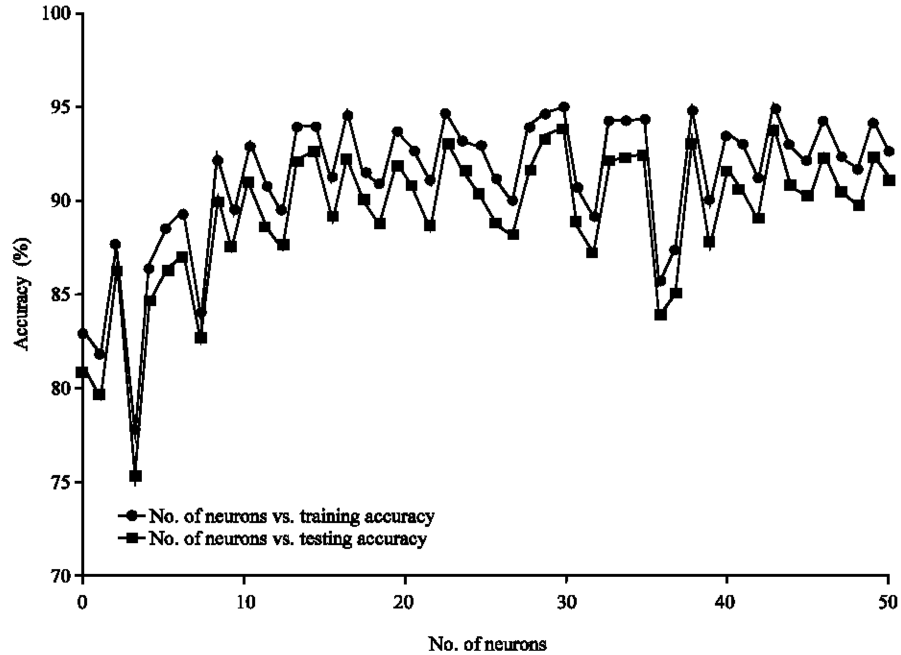

Fig. 6: Accuracy values versus the number of neurons

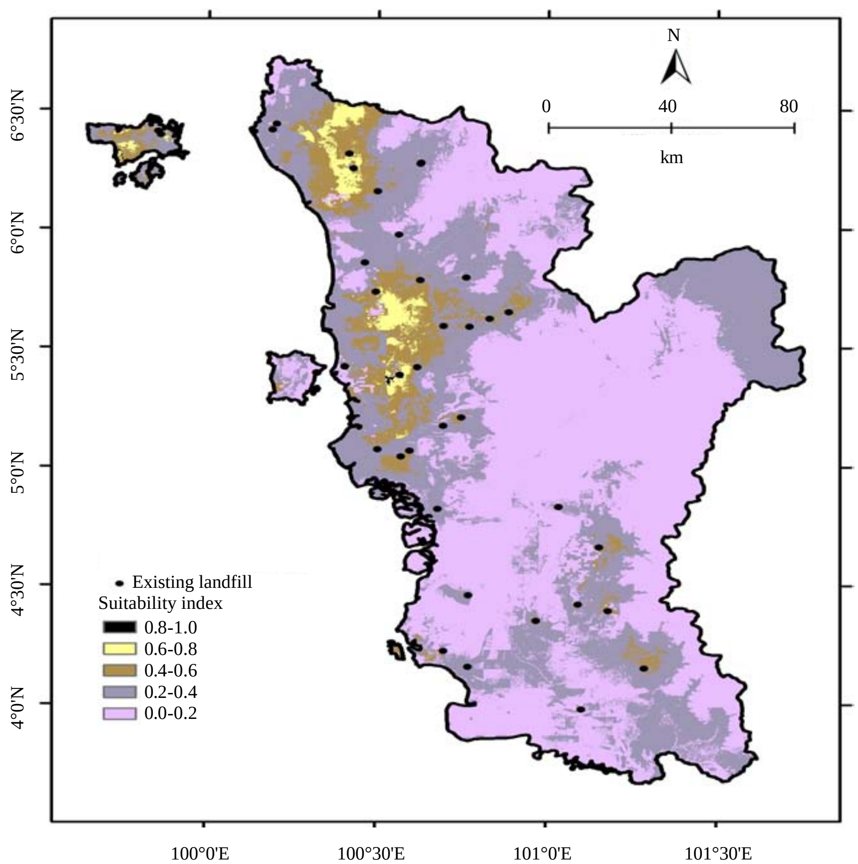

Fig. 7: Landfill suitability map

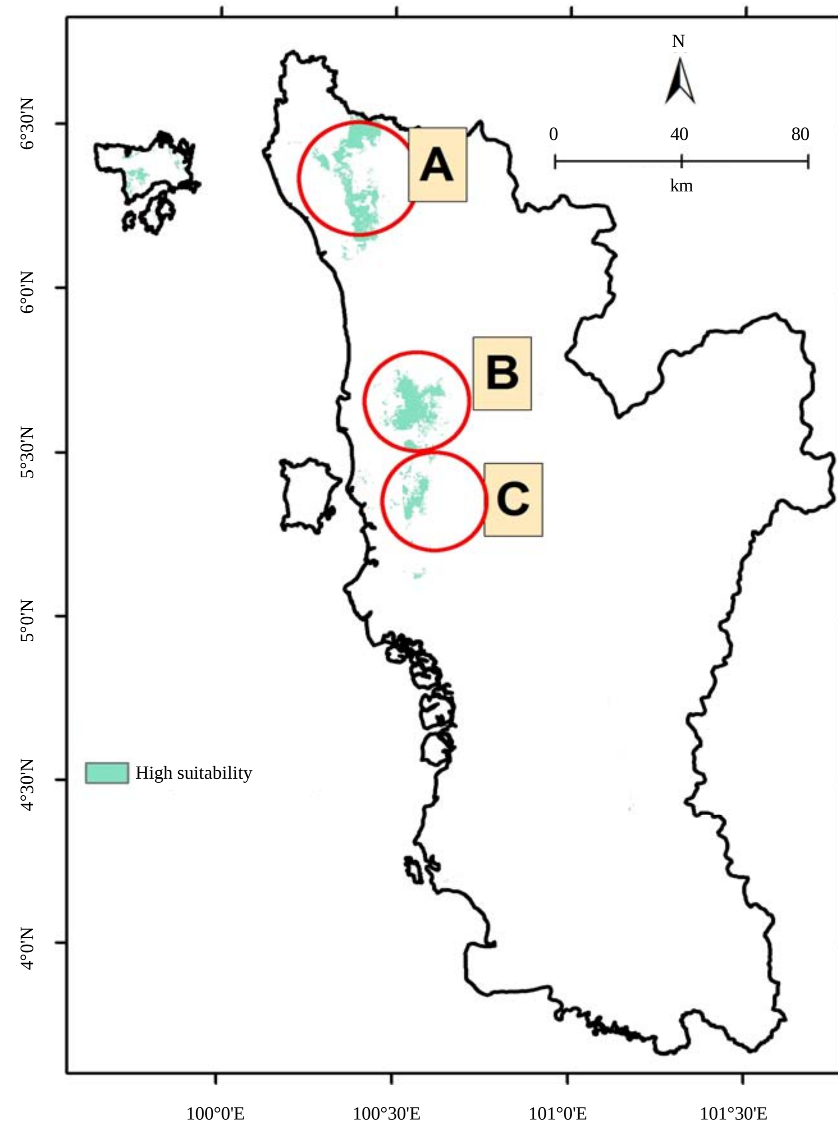

Fig. 8: High suitability areas

(37 out of 45) which support the robustness of HRCFNN. This landfill suitability map can assistance in the solid waste planning in the study area.

CONCLUSION

The objective of this study is propose hybrid network (HRCFNN), in order to improve the performance accuracy of solid waste suitability mapping. It is a combination between the Recurrent Neural Network and Cascade Forward Neural Network (HRCFNN). The methodology of combining the new network were described in detailed. The optimum structure of HRCFNN selected through finding the appropriate numbers of hidden layer neurons and the appropriate training function. Furthermore, the achieved performance outcomes revealed that the HRCFNN has no overfitting problem with high classification accuracy. The final structure of the HRCFNN introduced and used to produce the suitability index map which can be supports decision makers in the long-term plan developments. This outcome encouraged this study to utilize it in additional implementation for more reliability.

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