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DEVELOPING THE SELECTION OF THAI MEDICAL HERB SPECIES FOR COMMERCIAL CULTIVATION USING DEEP NEURAL NETWORKS

Sanya Khruahong and Tawin Tanawong*

Department of Computer Science and Information Technology
Faculty of Science
Naresuan University
99 Moo 9, Thapo Sub-district, Muang District, Phitsanulok 65000, Thailand
sanyak@nu.ac.th; *Corresponding author: tawint@nu.ac.th

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Abstract. *This research presents the deep neural network techniques for selecting commercial Thai medical herb cultivation species. This research was developed with three parts: 1) the data collection and variable selection, 2) the Deep Neural Network techniques to create a suitable model, and 3) the mobile application for selecting Thai herbs. Firstly, we collected 114 samples, of four Thai herbs. After that defines, the dependent variable is herbType and determines the predicted six variables. We found that the Correlation-based Feature Selection (CFS) is a variable for the dependent variable for modeling and is more suitable than the Information Gain (IG) method. Therefore, a sequence of relationships between the dependent and independent variables, i.e., Price, Duration, Mineral, Soil, Weather, and WaterSuffer, are 1.00, 1.00, 1.00, 0.40, 0.20, and 0.20, respectively. The experiment results obtained the best suitable model of Deep Neural Network is 6-3-3-4 with a momentum value of 0.2 and a learning rate of 0.3. The data is divided into learning and testing by 10-fold cross-validation; accuracy value is 79.55%, and the precision value is 78.90%. The experiment's findings have been successfully implemented into a mobile application for easy access and practical use.*
Keywords: Thai herbs, Deep learning, Deep neural network

1. **Introduction.** At present, the use of herbs is widely used both nationally and internationally. However, it was found that the herbal trade in the world market was worth up to 3.2 trillion baht. China is the largest producer of herbs, and the second is European countries, especially Germany, a recognized leader in herbal extraction and medical science. Herbs are used as an ingredient in treating up to 40% of primary diseases, and 45% [1,2] are substituted for modern medicine. For Thailand, it is used for domestic consumption and exports of herbs and processed products worth about 100 billion baht annually, or about 0.3%. In addition, medical and pharmaceutical knowledge has progressed rapidly, resulting in the discovery and application of many herbs, resulting in the use of herbs both directly and indirectly as ingredients of modern medicine [3]. However, the obstacles to growing Thai medicinal plants are still problematic because about 46% of Thai people still need to learn Thai herbs. About 88.8% believe that the government should support cultivating and developing Thai herbs to generate income for farmers. Moreover, many farmers need to be more successful in cultivating them, resulting in products that do not meet the market demand. Some farmers need to learn about land conditions unsuitable for growing herbs in some areas. Therefore, these problems should be solved with modern technology, such as machine learning, deep learning, or deep neural networks, which can analyze the types of medicinal plants suitable for cultivation in different environments.

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Deep Neural Networks (DNNs) [4-7] have been proposed to produce more predictive models. DNN architectures can be recognized for processing text, images, audio, and video. Deep Neural Networks (DNN) [8] were developed for grading the kiwi fruit flower with computer vision detection regarding fresh and rotting fruits. However, this paper got a suitable model with high accuracy but needs more information for analyzing other issues. Moreover, other neural networks, such as Fuzzy Neural Networks (FNN) [6], have been widely used for predicting the risk of losing student loans. Deep learning was applied to recognizing the desired herb among thousands of herbs which is an exhausting and time-consuming practice [9]. However, this article presented only Malaysian herbal leaves based on a classification system using ten features from the shape and texture. The stack autoencoder-deep neural network (SAE-DNN) [10] model was applied to predicting DTI in COVID-19 cases with good performance in Indonesia.

Therefore, the proposed prediction system aimed at aiding farmers in selecting herbs can benefit from using deep neural networks. This research is comprised of three main components: 1) gathering and selecting relevant data variables, 2) utilizing Deep Neural Network techniques to construct an appropriate model, and 3) creating a mobile application that allows farmers to select Thai herbs for commercial cultivation of medicinal plants.

This research investigates Deep Neural Network architectures that nearly overcome all the abovementioned challenges. The rest of this paper is organized as follows. Section 2 describes the proposed research methodology in detail. Reports on the performance of DNN are presented in Section 3. Section 4 discusses the experimental results. Section 5 presents the implementation. The final section concludes the paper.

2. **Research Methodology.** This research defines the concepts as shown in Figure 1. Use DNN techniques to select the type of cultivation of Thai commercial medicinal herbs with three parts. The first part is the data collection and variable selection by primary and secondary data collection methods. The appropriate independent variables were selected using the correlation technique using the Information Gain (IG or InfoGain) [11,12] model and Correlation-based Feature Selection (CFS) [13,14]. The second part is the DNN process from different hidden node classes to create a suitable model for creating rules and embedding code in applications. The third part is the mobile application implemented for selecting the cultivation of Thai medicinal herbs.

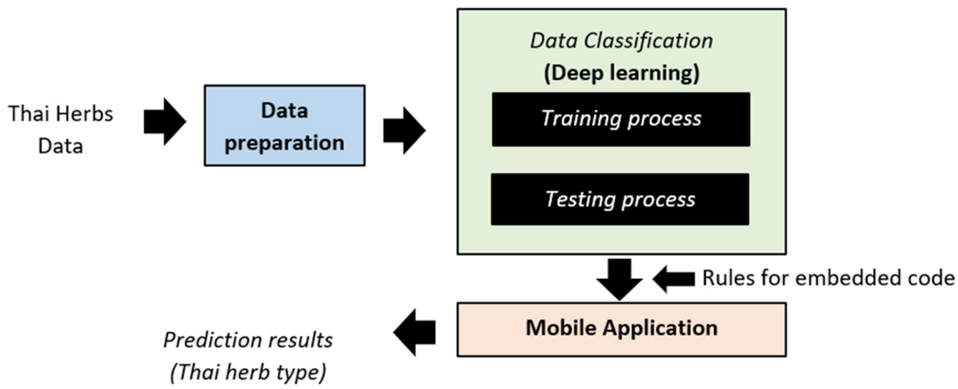

Figure 1. Overview of system process

2.1. **Data collection.** This paper collected 114 samples from farmers growing four types of Thai herbs. Attributes were selected by the sequencing method to reduce the number of attributes unrelated to the dependent variable by using the Weka program. This research has been compared in 3 models. Firstly, Pearson's correlation coefficient looks at the direction of the relationship between two variables, with the correlation coefficient (r) indicating this relationship. This value is between -1.0 and $+1.0$. A value near -1.0 means that the two variables are strongly correlated oppositely. If it is near $+1.0$, it means the two variables are related. It is straightforward, and if it is 0, the two variables are unrelated. Secondly, the feature subset selection selects some subset of attributes subsets from the total number of attributes. Thirdly, feature ranking calculates each attribute's score of feature score and sorts each attribute from highest to lowest.

The operation starts by sampling the entropy, where the information gain value is the difference between the target variable X and the independent variable A. The nature of the information gain reduces the entropy of the target variable X by learning from the state of the independent variable A. Information gain is more likely to select attributes with a high differential count than those with a low one. However, information gain computation considers an attribute X, a target variable, and an attribute that is a data class Y or an independent variable. It then examines the probabilities between the value of attribute X and the value of attribute Y. If the probability of occurrence is low, the rating of the X attribute is also low.

2.2. **Selection of variables.** Using Pearson's correlation coefficient [15,16] method of selecting variables, we will use Equation (1) to determine the degree of correlation. The correlation level is 1 or -1 as a perfect positive/negative correlation. A correlation level of 0.9 or -0.9 is a high positive/negative correlation. A correlation level of 0.5 or -0.5 is a low positive/negative correlation, and 0 is no correlation. This article finds that selecting predictive variables is related to the dependent variable. There are six variables in descending order of priority.

The 1) Duration variable is the period that those interested in growing medicinal plants want to harvest, which is most important in deciding to plant a medicinal plant. It may be due to the cultivator's desire for rapid production, or it may be separated from other crops. In addition, the order of importance was followed by 2) Price, 3) Mmineral is soil fertility, 4) waterSuffer is the level of adequacy of the water source required by plants, 5) Soil is a cultivated type, and 6) Weather with values 0.381, 0.294, 0.252, 0.232, 0.165 and 0.150, respectively.

Model 1: Pearson's correlation coefficient

$$r = \frac{(1/N-1)(\sum XY - ((\sum X)(\sum Y)/N))}{S_x S_y} \tag{1}$$

where r is the correlation coefficient, N is the number of samples, S_x is the standard deviation x, and S_y is the standard deviation y.

Model 2: In the case of calculating to select attribute A using information gain (Info-Gain), it is a measure used in decision tree learning algorithms to decide which feature to split on at each step in the tree-building process. The decrease in Entropy, or the amount of randomness or unpredictability in a system, results from making a particular decision.

$$\mathit{Gain}(Y, X) = H(Y) - H(Y|X) \tag{2}$$

where $H(Y)$ is the sampling probability of Y, $H(Y|X)$ is the sampling probability of Y for X, and $\mathit{Gain}(Y, X)$ is the calculated sampling score value from 0 to 1, Y represents the value of an attribute class of calculated data $\{Y_1, Y_2, \dots, Y_n\}$.

The value of X is the value of attributes other than the class $\{X_1, X_2, \dots, X_n\}$. Values of $H(Y)$ and $H(Y|X)$ are calculated from

$$H(Y) = -\sum_{j=1}^{J=k} P(Y - y_j) \log_2 P(Y = y_j) \tag{3}$$

$$H(Y|X) = -\sum_{j=1}^{J=k} P(Y - x_j)H(Y|X = x_j) \quad (4)$$

$P(Y = y_j)$ is the probability from y_1 to y_k, and $H(Y|X = x_j)$ is the probability from x_1 to x_k. The selection of predictive variables that correlate with variables followed by the InfoGain method reveals that the forecast variables have a sequence similar to the correlation method but differ from 6 onwards. It is most important to decide on the cultivation of medicinal plants. These may be because the cultivator wants to produce quickly or a time-separator. After all, other crops are grown. In addition, the order of secondary importance is Duration, Price, WaterSuffer, Mineral, Soil, and Weather, with values of 0.900, 0.447, 0.350, 0.331, 0.146, and 0.139, respectively.

Model 3: Correlation-based Feature Selection (CFS) is a technique that uses the determination of a group of attributes evaluated based on predictability by the attributes chosen for the data classification.

$$M_s = \frac{k\overline{r_{cf}}}{\sqrt{k + k(k-1)\overline{r_{ff}}}} \quad (5)$$

where M_s is the lookup value of the subgroup dimension s, which consists of dimension k, $\overline{r_{cf}}$ is the mean correlation of variables with classes ($f \in s$), and $\overline{r_{ff}}$ is the mean correlation between data dimensions.

It is found that the selection of independent variables correlates with variables. There are six selected forecast variables, with other predictive variables being eliminated by the CFS program. The number of predictive variables obtained is Soil, Weather, Price, WaterSuffer, Duration, and Mineral.

Table 1. A comparison of independent variable selection methods

Independent variable details before selection	Method for selecting independent variables					
	Pearson's correlation		Correlation-based Feature Selection (CFS), cross-validation fold (10)		Information Gain (IG)	
	Order of independent variables	Correlation values	Order of independent variables	Correlation values	Order of independent variables	Correlation values
Soil	Duration	0.381	Price	Fold(5) 100%	Duration	0.900
Weather	Price	0.294	Duration	Fold(5) 100%	Price	0.447
AreaSize	Mineral	0.252	Mineral	Fold(5) 100%	WaterSuffer	0.350
Market	WaterSuffer	0.232	Soil	Fold(2) 40%	Mineral	0.331
Price	Soil	0.165	Weather	Fold(1) 20%	Soil	0.146
WaterSuffer	Weather	0.150	WaterSuffer	Fold(1) 20%	Weather	0.139
InsecQuantity	AreaSize	0.117	InsecQuantity	Fold(0) (0%)	AreaSize	0
Duration	InsecQuantity	0.110	AreaSize	Fold(0) (0%)	InsecQuantity	0
Knowledge	Market	0.094	Knowledge	Fold(0) (0%)	Experience	0
Experience	Experience	0.077	Experience	Fold(0) (0%)	Knowledge	0
Mineral	Knowledge	0.059	Market	Fold(0) (0%)	Market	0

2.3. Creating prediction model with deep neural networks.

- Input is numeric data. If it is qualitative, it must be converted to a quantitative form.

- Output is the result of learning a neural network.

- Weights are learned by neural networks, also known as *knowledge values*. This value is stored as a skill for use in remembering other information.

- Summation function ($\boldsymbol{S}$) is the sum of imported data (a_i) and heavy lead (w_i).

$$S = \sum_{i=1}^{n} a_i w_i \tag{6}$$

- Transfer function is a calculation of the simulation of neural networks such as the sigmoid function, where the result is a range between 0-1 hyperbolic tangent function.

Select a data breakdown model to measure the performance of the model. In this research, we selected two main data divisions: the Split Test format using 34%, 70%, and 80% coaching sample data, using 66%, 30%, and 20% test samples, respectively, and the Cross-validation Test format, where we determined Fold = 5 and Fold = 10 respectively and the 6-3-3-4 deep neural network structure model.

3. **Performance of Deep Neural Network (DNN) Models.** According to this research, the most suitable deep neural network model is shown in Table 2. A 6-3-3-4 deep neural network structure uses a model of independent variable selection with CFS. It divides the data in a 10-fold cross-validation manner, with a momentum value of 0.2, a learning rate of 0.3, and an accuracy value of 79.55% and 78.90%, respectively. The weight attributes of the model are detailed, as shown in Table 3, Table 4, and Table 5, respectively.

Table 2. The deep neural network structure patterns

Test options		**Classifier formats**	**Accuracy (%)**	**Precision (%)**
Percentage split 30%	CFS	6-3-4-4	59.12	51.90
		6-5-5-5-4-4-4	23.94	5.70
	IG	6-3-4-4	60.56	51.30
		6-5-5-5-2-3-4	23.94	5.70
	Pearson's correlation	6-3-4-4	69.01	69.50
		6-2-4-3-3-5-4	23.94	5.70
Percentage split 66%	CFS	6-4-5-4	60.00	48.10
		6-4-4-4-5-5-4	25.71	6.60
	IG	6-5-2-4	60.00	48.10
		6-5-5-3-3-4-4	25.71	6.60
	Pearson's correlation	6-3-4-4	68.57	78.60
		6-3-3-4-4-5-4-4	25.71	6.60
Cross-validation 5-folds	CFS	6-5-3-4	69.61	69.70
		6-3-3-5-5-5-4	33.33	11.10
	IG	6-5-5-4	68.64	69.60
		6-5-5-4-4-4-4	33.33	11.10
	Pearson's correlation	6-3-5-4	63.73	62.90
		6-3-5-5-4-4-4	33.33	11.10
Cross-validation 10-folds	CFS	6-3-3-4	79.55	78.90
		6-5-5-4-4-4-4	32.35	19.40
	IG	6-4-4-4	68.34	69.10
		6-4-4-4-5-5-4	32.35	19.40
	Pearson's correlation	6-3-3-4	66.67	68.60
		6-4-3-3-5-5-4	32.35	19.40

Table 3. The weight between the input node and the hidden node

Node type	**Soil**	**Weather**	**Price**	**WaterSuffer**	**Duration**	**Mineral**	**Threshold**
SigmoidNode4	1.62	0.76	−11.23	2.26	12.96	9.52	−2.87
SigmoidNode5	2.02	−2.09	1.89	−0.38	−8.13	0.06	−1.48
SigmoidNode6	2.81	−3.59	2.77	−1.22	−8.28	0.42	−1.34

Table 4. The weight between a hidden node and a hidden node

SigmoidNode7	SigmoidNode8	SigmoidNode9
Node 4: 1.49	Node 4: −3.26	Node 4: −11.65
Node 5: −5.08	Node 5: −3.56	Node 5: −2.69
Node 6: −4.24	Node 6: −5.03	Node 6: −4.00
Threshold: 5.02	Threshold: 2.27	Threshold: 2.32

Table 5. The weight between a hidden node and an output node

SigmoidNode0	SigmoidNode1	SigmoidNode2	SigmoidNode3	SigmoidNode7	SigmoidNode8	SigmoidNode9
Node 7: 2.44	Node 7: 3.21	Node 7: −7.80	Node 7: 3.58	Node 4: 1.49	Node 7: −3.26	Node 7: −11.65
Node 8: 1.70	Node 8: 2.52	Node 8: −4.89	Node 8: −2.50	Node 5: −5.08	Node 8: −3.56	Node 8: −2.69
Node 9: 7.63	Node 9: −7.72	Node 9: −2.03	Node 9: −1.34	Node 6: −4.24	Node 9: −5.03	Node 9: −4.00
Threshold: −5.90	Threshold: −3.40	Threshold: 5.02	Threshold: −3.17	Threshold: 5.02	Threshold: 2.27	Threshold: 2.32

4. **Experimental Results.** In order to use the resulting value to calculate the model's forecast, Table 6 represents a sample of the input data to predict the result under the determination of the variable accordingly, the value of herbType for Table 7. For example, Soil has max = 5 and min = 1, so the range value is equal to 2 for finding the base value from $(\max + \min)/2$; that is, Soil has max = 5 and min = 1, so the base value is equal to 3 for the *norm_Attri* from $(attrsoil - base)/range$, that is, the *attrsoil* example is equal to 1, and the base value is −3, so the range value is equal to −1.

Table 6. Example of a data presentation for the selection of Thai medicinal plant species

Soil	Weather	Price	WaterSuffer	Duration	Mineral	herbType
1	2	120	1	4	1	?

Table 7. The data for use in DNN with patterns 6-3-3-4

	Soil	Weather	Price	WaterSuffer	Duration	Mineral
range	2	3	96.5	1	2	1
base	3	4	103.5	2	3	2
norm_Attri	−1	−0.67	0.17	−1	0.5	−1

Therefore, in this research, the researchers showed examples of imported data to examine the forecast results of the model. The number of test data is shown in Table 8, and the forecast results can be displayed as shown in Table 9. In this study, we evaluate the performance of a deep neural network structured as DNN (6-3-3-4) employing CFS variable selection. We compare this against DNN models with configurations (6-5-5-4) utilizing the Information Gain (IG) method for variable selection patterns and DNN (6-3-4-4) employing Pearson's correlation for variable selection. It can be concluded that the sample data introduced into the forecasting system using the DNN (6-3-3-4) selected variables with CFS is the most accurate predictive performance value. The results matched the data in the second, third, fourth, fifth, sixth, seventh, eighth, and ninth samples. The DNN model (6-3-4-4) selectively selects variables with Pearson's correlation for the deep neural network technique. The result of predictive performance values accurately matches the data in the second, fourth, eighth, and ninth import samples. For the DNN (6-5-5-4) deep neural network technique, selecting variables with IG had predictive performance values accurately matching the actual data in the fourth, sixth, eighth, and ninth samples, respectively.

TABLE 8. Samples of type selection of Thai herbs in commercial forecasts with DNN

Data sample	Soil	Weather	Price	WaterSuffer	Duration	Mineral
Input(1)	4	3	82	1	5	1
Input(2)	1	3	60	1	5	1
Input(3)	3	2	150	1	4	1
Input(4)	1	5	80	1	4	1
Input(5)	1	2	120	1	4	1
Input(6)	3	5	50	3	3	1
Input(7)	4	3	35	1	2	2
Input(8)	3	3	40	1	1	2
Input(9)	3	5	30	2	1	2
Input(10)	3	5	20	2	1	2

TABLE 9. Prediction results of DNN

Input samples data	The DNN (6-3-3-4) CFS attribute selection		The DNN (6-5-5-4) IG attribute selection		The DNN (6-3-4-4) Pearson's correlation attribute selection		The actual data
	Generated data	Probability	Generated data	Probability	Generated data	Probability	
Input(1)	Plai	0.008	Plai	0.258	Plai	0.055	centellaAsiatica
Input(2)	Plai	0.118	blackGalingale	0.712	Plai	0.079	Plai
Input(3)	Plai	0.104	blackGalingale	0.983	blackGalingale	0.954	Plai
Input(4)	blackGalingale	0.915	blackGalingale	0.965	blackGalingale	0.971	blackGalingale
Input(5)	turmeric	0.844	blackGalingale	0.944	blackGalingale	0.965	turmeric
Input(6)	blackGalingale	0.929	blackGalingale	0.005	turmeric	0.039	blackGalingale
Input(7)	Plai	0.017	centellaAsiatica	0.005	centellaAsiatica	0.005	Plai
Input(8)	centellaAsiatica	0.136	centellaAsiatica	0.005	centellaAsiatica	0.025	centellaAsiatica
Input(9)	centellaAsiatica	0.480	centellaAsiatica	0.005	centellaAsiatica	0.006	centellaAsiatica
Input(10)	centellaAsiatica	0.477	centellaAsiatica	0.005	centellaAsiatica	0.004	blackGalingale

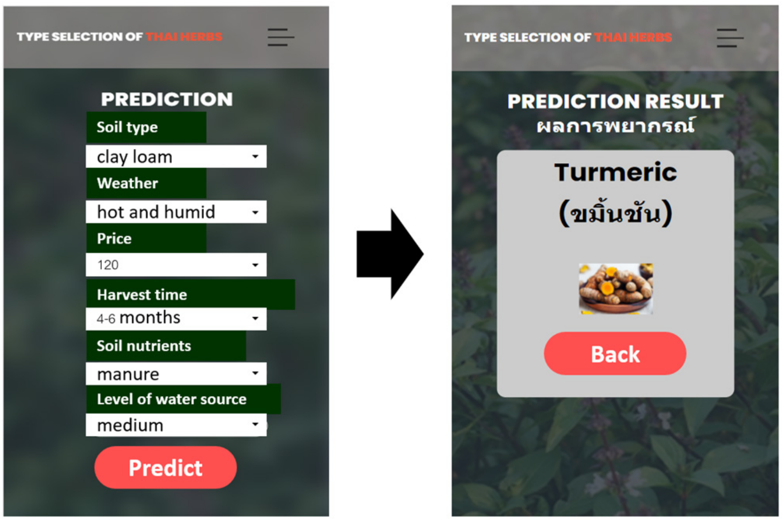

FIGURE 2. Mobile application for selecting Thai herbs

5. **Implementation.** After the research results in various aspects, those data were used to develop a mobile application for users to contemplate Thai herb cultivation by selecting different conditions and observing the predicted outcomes, as depicted in Figure 2.

6. **Conclusion.** In conclusion, this research successfully presented a Deep Neural Network approach for selecting commercial Thai medical herb cultivation species, which consisted of three main parts: 1) data collection and variable selection, 2) DNN techniques for creating a suitable model, and 3) a mobile application for selecting Thai herbs. The study collected 114 samples, including four Thai herbs by farmers, and determined the dependent variable (herbType) and predicted six variables. The Correlation-based Feature Selection (CFS) was a more suitable variable for modeling than the Information Gain (IG) method. The experiment also identified relationships between the dependent and independent variables. The best suitable model of a Deep Neural Network was 6-3-3-4 with a momentum value of 0.2 and a learning rate of 0.3. The data was divided into learning and testing by 10-fold cross-validation: an accuracy value is 79.55%, and a precision value is 78.90%. The average value of an independent variable correlated with a dependent variable is 0.630. The IG method is 0.385, and Pearson's correlation method is 0.246. Finally, information from the experiment is implemented into a mobile application, which can support herb farmers in selecting Thai medical herb species.

In future work, the model's performance needs to be further developed because the amount of sample is insufficient, and the initial independent variables are defined for selection by different methods. Therefore, it is essential to improve the data model and independent variables to be more relevant to the variables and to have a sufficiently large number of sample data.

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