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Modelling the Maturity Levels of Farmer Groups Using Artificial Neural Networks

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Abstract: ***This paper sets to develop an artificial neural networks model that predicts the performance of farmer groups i.e. whether beginner, intermediate or mature depending on the groups level of performance. Five broad classes of variables were used namely governance, management, leadership, resilience and capacity development. Data was collected through random sampling from farmer groups in East Africa. Two districts were involved from each country, mainly targeting districts where the International Funding for Agricultural Development had ongoing activities. A model with an overall accuracy 97% was developed and was effective in prediction of various farmer organizations' classes using the variables identified.***

Keywords: performance levels, farmer groups, neural networks, Capacity needs assessment.

1. Introduction

In all research problems, scientists are interested in deriving information from data sets by exploring the patterns and investigating relationships between the various data sets. The information obtained is hoped to be useful in the decision making process and management (Kipruto 2006).One such example is in farmer groups' performance, where researchers are interested in the various variables that affect their performance. They are also interested in the type of relationships that exist between these variables and performance of farmer groups. Such relationships answer questions such as the effect of governance, leadership, Education, etc. on collective action which is appreciated through the farmer groups to provide farmers with services that support their farming activities (Kassam et al. 2007).

The problem is to find an association between the multivariate data set variables and evaluation of possible association between them. From the literature reviewed it emerged that researchers dealing with such multivariate relationships especially with farmer organizations tend to stop at data analysis without developing statistical models or other statistical tools that can be used in the long run. Despite comprehensive literature on the subject, the range of analysis methods used remain limited and tend to be predominantly linear regression. In general it is good to appreciate the fact that statistical modeling has not been applied exhaustively in the assessment of community collective action. This study thus sets out to develop an artificial neural networks model that explains the performance of farmer groups as part of a contribution to the wanting farmer groups' performance.

2. Methodology

Data Collection

The study used data on farmer groups collected through random sampling in East Africa. The study emphasized on a participatory methodology in which fives broad categories of variables namely governance, management, leadership, resilience and capacity development were developed, each with a set of indicators of performance within them to allow for farmer organizations and stakeholders to select those that were relevant to their research sites as summarized in table 1.

Table 1: Variables used in measuring maturity levels by SRI.

Variable	*Criteria*
Governance	Group registration, funding process, entry policy, exit policy, Leadership succession rules, Members' terms of references, upward mobility
Management	Key production/delivery and support, group contracts, MOUs with partners, program description, resource availability, profit re-investment
Leadership	Styles of leadership, member's responsibilities, influence of public perception, organizational performance and improvement in its key business areas, partnership performance and performance with partners, competitors and after ceasing of funding
Capacity Development	Dissemination of information and communication (to members and to the members of the public), organizational learning and capacity building, types of training programs and expertise in the group
Resilience	Achieving equity through heterogeneity in membership, adaptive capacity and accumulated asset records.

The Neural Networks Model

Artificial neural networks have been useful in explaining a wide range of relationships and are based on an effort to model the way a biological brain processes data and are thus dissimilar from other normal regression models. Their applications include:

- **Forecasting:** predicting one or more quantitative outcomes from both quantitative and categorical input data,
- **Classification:** classifying input data into one of two or more categories, or
- **Statistical pattern recognition:** uncovering patterns, typically spatial or temporal, among a set of variables.

Numerous studies have indicated that ANN models represent a promising modeling technique especially for data sets having non-linear relationships (Asnaashari 2013). A vital component in creating an ANN model is the number of hidden nodes, which defines the complexity of the model developed (Despagne and Massart1998). In this case, the modeling process for ANN was adapted through the following steps:

1. A record of farmer groups was first generated and distributed randomly into three distinct categories with 0.5 used for training, 0.25 for testing, and the remaining 0.25 used for validation as shown in table 2.

Table 2: Data used in Modelling

Task	Training	Testing	Validation	Total
No. of farmer groups	0.5	0.25	0.25	1

2. Developing the basic architecture/structure of the ANN model using an input layer, output layer and the number of hidden layers as shown in figure 1.

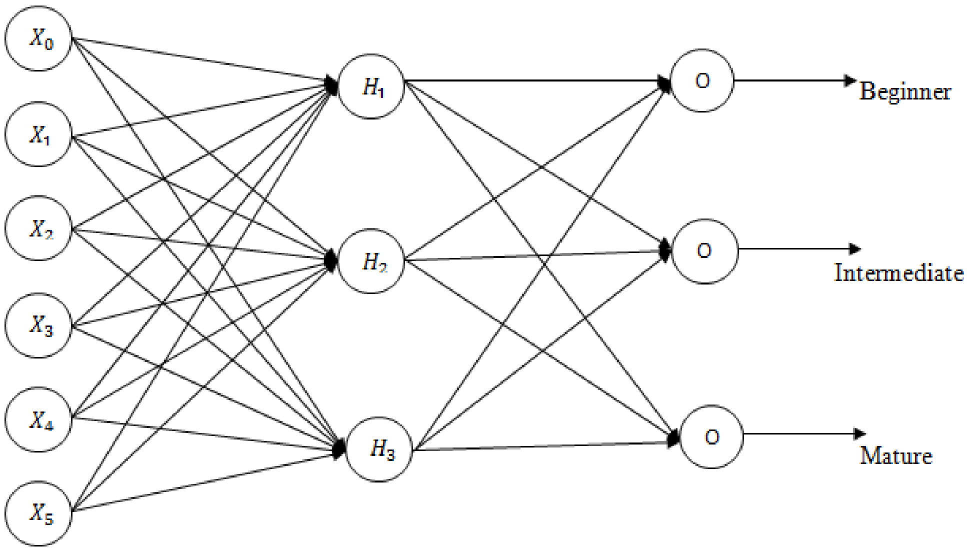

Figure 1: Schematic representation of the ANN architecture

3. The third step involved drilling and testing the ANN model to create the optimal structure, which included determining the optimal number of hidden nodes and iterations.

Training of the Network

The SSE is normally used in training faced forward networks. In this method the weights are adjusted in such a way that the SSE between the targets and the goal of output $Y = (Y_1, \ldots, Y_{134})$ is minimized.
The SSE is defined as:

$$S^2(X_{i\alpha}; \beta) = \sum (Y_i - \gamma(X_{i\alpha}; \beta))^2$$
$$= \sum (Y_i - \gamma(X_{i\alpha}; W, \theta))^2$$
$$= \sum (Y_i - \gamma(\theta_0 + \sum_{j=1}^{H} \theta_j \phi_h (W_{j0} + \sum_{i=1}^{5} W_{ji} X_{i\alpha}^{*})))^2 \quad (1)$$

There are various methods of minimizing this function namely;
1. Back Propagation
2. Quasi Newton Method
3. Simulated Annealing Method

The bipolar activation function was combined with the Quasi Newton method in minimizing the SSE. In this method, the training starts by imputing an initial set of weights, β^0. Fromβ^0, $S^2(X_{i\alpha}; \beta^0)$ is then determined.

From the principles of second-order Taylor operation, $S^2(X_{i\alpha}; \beta^1)$ can be found as follows:
A_0 Will be defined as:

$$A_0 = \frac{S^2(X_{i\alpha}, \beta^{0,1} + m_1, \ldots, \beta^{0,q}) - S^2(X_{i\alpha}, \beta^{0,1}, \ldots, \beta^{0,q})}{m_1}$$
$$= \frac{S^2(X_{i\alpha}, \beta^{0,1}, \ldots, \beta^{0,q} + m_1, \ldots, \beta^{0,q}) - S^2(X_{i\alpha}, \beta^{0,1}, \ldots, \beta^{0,q})}{m_q}$$
$$= \frac{S^2(X_{i\alpha}, \beta^{0,1}, \ldots, \beta^{0,q} + m_q) - S^2(X_{i\alpha}, \beta^{0,1}, \ldots, \beta^{0,q})}{m_q} \quad (2)$$

Where $m_q = \max(\epsilon, \epsilon\beta^{0,q})$ with $\epsilon = 10^{-6}$ for q=1, 2… q and i=1…n
The hessian matrix B_0 for the SSE is then defined with the direct off-diagonal elements evaluated as follows:

$$\frac{\partial^2 S^2(X_{i\alpha};\beta^0)}{\partial\beta^{0,j}\,\partial\beta^{0,k}} = \frac{1}{m_j m_k}\{S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}+m_j,\dots,\beta^{0,k}+m_k,\dots,\beta^{0,q}) - S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j},\dots,\beta^{0,k}+m_k,\dots,\beta^{q}) - S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}+m_j,\dots,\beta^{0,k},\dots,\beta^{0,q}) - S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,q})\}$$

For $j,k = 1,\dots,q$ and $i = 1,\dots,n$ (3)

The direct diagonal elements of B_0 on the other hand are evaluated as:

$$\frac{\partial^2 S^2(X_{i\alpha};\beta^0)}{(\partial\beta^{0,j})^2} = \frac{1}{m_j m_k}\{S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}+m_j,\dots,\beta^{0,q}) + S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,j}-m_j,\dots,\beta^{0,k},\dots,\beta^{0,q}) - 2S^2(X_{i\alpha};\beta^{0,1},\dots,\beta^{0,q})\}$$

For $j,k = 1,\dots,q$ and $i = 1,\dots,n$ (4)

$\beta^1$is then obtained by differentiating the right hand side of equation (5) with respect to $\beta^1 - \beta^0$ and equating the result to zero to get:

$$\beta^1 = \beta^0 - B_0^{-1}A_0 \quad (5)$$

The iteration then continues from iteration 1 to 2 until the stopping criterion is met. In general the r^{th} iteration would be given by:

$$\beta^{r+1} = \beta^r - B_r^{-1}A_r \quad (6)$$

Incase during the iteration, the Hessian matrix B becomes non-singular, equation (6) is redefined as follows:

$$\beta^{r+1} = \beta^r - W_r B_r^{-1}A_r \quad (7)$$

Where W_r is the step length and is found such that:

$$S^2(X_{i\alpha};\beta^r - W_r B_r^{-1}A_r) < S^2(X_{i\alpha};\beta^r) \quad (8)$$

This is done using the step halving method in which W_r is first set to one and the function $S^2(X_{i\alpha};\beta^r - W_r B_r^{-1}A_r)$ tested for a decrease. If it fails W_r is decreased by ½ and the test carried out again. The process continues until a decrease in the function occurs. The final value of W_r is the required step length.

By letting the change in parameters $(\beta^{r+1} - \beta^r)$ be:

$$a_r = -W_r B_r^{-1}A_r$$

And

$$b_r = A^{r+1} + A^r \quad (9)$$

The Quasi Newton condition is then be given by:

$$B_{r+1}a_r = b_r \quad (10)$$

Note that the Quasi Newton condition is the ratio of the change in gradient to the change in parameters.

The Quasi Newton method solves equation (11) for B_{r+1} as:

$$B_{r+1} = B_r + \frac{b_r b_r^t}{b_r^t a_r} - \frac{B_r a_r a_r^t B_r}{a_r^t B_r a_r} \quad (11)$$

This continues until the termination criterion is satisfied. The termination criteria in this study included fixing the maximum number of iterations to be attained.

4. A comparison of the statistical accuracy of the calculations from the training, testing and validation phases was then done.

5. The fifth step then involved checking if the statistical accuracy from training, testing, and validation sets were comparable and if they were found not to be, the process was repeated starting with the third step otherwise, an ANN model with an acceptable structure for the desired model was created. Supervised learning was used to train the network because the program knows the outputs it will be trying to calculate, as opposed to unsupervised learning where the outputs are usually unknown.

3. Results and Discussion

As identified in the methodology, data for ANN modeling was divided into 3 categories with 50% for ANN drilling, 25% (67groups) for testing and another 25% for the validation process. Different trials were done in drilling to get the finest possible values for different number of hidden nodes and learning rates for the back propagation algorithm. The error parameter with respect to the number of iterations for various learning rates and number of hidden nodes was noted. At first the value of learning rate was varied keeping the number of hidden nodes constant. Then the number of hidden nodes was varied keeping learning rate constant. The optimal learning rate and number of hidden node were found to be 0.01 and 10NHN respectively. The results from training, testing and validation were compared to verify whether there was consistency in the model developed and summarized as shown in table 3.

Table 3: results from ANN training, testing and validation

		ANN Training			ANN Testing			ANN Validation		
		B	I	M	B	I	M	B	I	M
Original output	B	7	0	0	1	0	0	5	1	1
	I	0	49	0	2	25	1	0	26	0
	M	0	0	11	0	0	5	0	0	3

In general the performance measures from training, testing and validation of the neural networks model were summarized as in table 4.Results indicate a validation accuracy of 97%

Table 4: ANN Performance measures in training, testing and validation

		Testing			Validation		
		Accuracy	True Rate	Precision	Accuracy	True Rate	Precision
Expected output	Beginner	94.03%	1.0000	40%	97.06%	0.8462	100%
	Intermediate		0.9273	100%		1.0000	98%
	Mature		1.0000	90.9%		1.0000	85.71%

4. Conclusion

This paper offers empirical insight on how the performance of farmer groups can be evaluated through mathematical modelling. There exists a relationship between governance, management, leadership, capacity development and resilience and the performance of farmer groups. This findings advocate for greater recognition of the importance and application of statistical methods in the agricultural sector as well as a participatory approach in capacity building through the development of farmers. The model developed will be applied in the capacity needs assessment of farmer organization in determining their maturity levels.

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