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Developing a Model to Predict Success of Agricultural Production Enterprises Based on Their Capitals

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ABSTRACT

This study aimed to develop a recognition model in order to classify success of agricultural enterprises. To this end, the study investigated the relationship between capitals owned by the enterprise and the success level by using "Neural Network" model. This study was conducted during 2013-2014 in Zanjan County, Islamic Republic of Iran. Data was obtained through a structured questionnaire and holding interviews with 92 enterprise owners, out of 125, involved in producing agrifood. According to the results of data analysis, Multilayer Perceptron Neural Network with Backpropagation algorithm was the appropriate algorithm to cope with the whole scope of the study. Empirical analysis by SPSS indicated that the Multilayer Perceptron consisting of one hidden layer with 6 nodes was an appropriate architecture. Classification Accuracy Rate (CAR) and "Receiver Operating Characteristic (ROC)" curve were used to assess the model. Based on CAR of holdout data, the model was able to classify 86.4% of the samples correctly. Also, the study intended to reveal the relative importance of explanatory factors on enterprise success. Results indicated that human and social capitals were the more influential factors, followed by economic and environmental capitals. Therefore, to promote agricultural enterprises, policy makers and managers need to improve software and hardware assets, simultaneously.

Keywords: Classification, Neural Network, Perceptron, Pattern.

INTRODUCTION

In Iran, agriculture still constitutes the backbone of the rural economy and it represents a major source of employment and generates notable earnings. Investment in agriculture has been enhanced for many years via granting loans by Agricultural Bank (Pishbahar *et al*., 2015). Within this study area, i.e. Zanjan County, subsidy loans have been paid to promote agricultural enterprises; however, field observations show that these enterprises have experienced differential performances. As a consequence, owners of these enterprises do not feel the same level of success. These differences were the basic motivation for conducting this study. This study aimed to develop a recognition model to explain and classify enterprises based on their success levels. Developing the model would help in taking appropriate policy measures. Explanatory factors, generally, have different importance in the model. So, investigation of the importance of the factors is another purpose of this study.

Within the present research's scope, there are some methods including Multiple Discriminant Analysis (MDA), logistic regression and Neural Network (NN) models. NN models have beneficial properties for modeling such as resistance to

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missing data, accommodation of multiple non-linear variables with unknown interactions and good generalization ability (Safa *et al*., 2015). In comparison to classical and traditional methods, NN models are relatively new classification techniques, which do not require a priori assumptions regarding the underlying data distribution or the structure of the relation between the variables involved and do not require the researcher to identify the functional relationship between dependent and independent variables. Studies argue that for real world classification tasks and business failure prediction studies, NN models have performed well and they are strong alternatives to classic methods and should be considered (Youn and Gu, 2010). Multi-Layer Perceptron (MLP) with feed-forward back-propagation algorithm, a type of NN models, is the most commonly used model in classification issues (Charalambous *et al*., 2000; Zhao *et al*., 2012; Anandarajan *et al*., 2001) and where dependent variable is nominal or categorical (Tang and Chi, 2005; Cao *et al*., 2011). So, MLP has been used in this study.

Success is traditionally defined in terms of financial performance (Reijonen and Komppula, 2007) while some studies indicate many entrepreneurs consider factors other than profits and financial growth in statement of their success (Paige and Littrell, 2002) and they envisage non-financial measures such as autonomy and job satisfaction more than financial indicators (Reijonen and Komppula, 2007). Success, in prior studies, has been measured by the wealth creation, businesses creation, existing business promotion, sale growth, profitability, income increasing, return on investment, productivity, loan repayment, employment, satisfaction, self-reliance, and goal realization (Paige and Littrell, 2002; Sandberg, 2002; Van Praag, 2003; Reijonen and Komppula, 2007; Nichter and Goldmark, 2009). These studies only have considered limited dimensions and indicators to measure the success. The present study takes a somewhat different approach and attempts to consider environmental, economic, social, and human aspects in order to measure the success. On the other side, this study also aims to have relatively comprehensive approach in order to investigate the underlying factors that explain the success.

Literature review reveals that success may be explained by some environmental and domestic factors. Success caused by the presence, availability, and interplay of capitals including Environmental Capital (EnC), Human Capital (HC), Social Capital (SC) and Economic Capital (EC) (Van Praag, 2003; Anderson and Miller, 2003; Darroch and Clover, 2005; Kaasa and Parts, 2008; Unger *et al*., 2011; Martin *et al*., 2013). These capitals are defined as follows:

EnC: *EnC* refers to environment ability, natural resource quantity and quality, productive infrastructure, communication facilities, remoteness or peripheral (Agarwal *et al*., 2009; Mauerhofer, 2008).

EC: *EC* refers to the capital required for agricultural production, such as land, buildings and machinery (Martin-Collado, *et al*., 2014).

HC: *HC* refers to the individual's ability and quality. HC is a main factor of the start, growth and success of a business and consists of education, experiences, entrepreneurship orientations and useful skills (Unger *et al*., 2011; Javalgi and Todd, 2011; Martin *et al*., 2013).

***SC*:** *SC* refers to norms, trust, reciprocity, connections and networks (Agarwal *et al*., 2009), cooperation and participation, mutual aid and helping, membership in groups, contacts (Krishna, 2004; Van Rijn *et al*., 2012). It is has the potential to enhance the benefits of investment in other forms of capital (Agarwal *et al*., 2009). *SC*, as a private good extracted from the group, affects the productivity (Svendsen, *et al*., 2010), reduces transaction costs and facilitates access to other capitals (Magnani and Struffi, 2009).

Architecture of MLP: It requires identifying the number of layers and nodes, optimization algorithm, transfer function, and sample partition, as follows:

Input and Output Layer Nodes: The number of input nodes is equal to the number of attributes (Keyvanpour *et al*., 2011) and the number of output nodes is equal to the number of classes (Setsirichok *et al*., 2012).

Hidden Layer Nodes: There is no theoretical guidance (Jiuju, 2013) to estimate the optimum number of the hidden layer nodes. It is somehow practically proved that the number of hidden nodes should equal at least the number of input variables in order to capture 70–90% of the variance on the input data (Brouthers *et al*., 2009). The number of hidden nodes is set to [(Number of attributes+number of classes)/2] (Setsirichok *et al*., 2012) and also Classification Accuracy Rate (CAR) of the hold-out samples (Youn and Gu, 2010) is used in classification issue.

Hidden Layer: It can be proved that having one hidden layer is sufficient to approximate any linear or non-linear function (Keyvanpour *et al*., 2011) and any complex system (Lu and Wu, 2011).

Network Training: There are two practical training ways to implement the back propagation algorithm: batch updating approach and online updating approach (Wu *et al*., 2011; Nakama, 2009). Batch training seems faster for small-size training sets, online training is probably more efficient for large training sets (Wilson and Martinez, 2003; Magoulas *et al*., 2004).

Optimization Algorithm: Scaled Conjugate Gradient (SCG) and Levenberg–Marquardt (LM) are typically applied to optimize a MLP (Beale *et al*., 2010), and there are no certain results regarding their relative superiority, though in one reference (Zhao *et al*., 2012) the LM is highlighted. On the other hand, *SCG* is preferred for pattern recognition issues (Beale *et al*., 2010) and widely applied with feed-forward back propagation architecture (Khataee and Kasiri, 2011).

Activation Function: typically, hyperbolic tangent activation function and sigmoid activation function applied for studies of classification issue and also firm performance (Brouthers *et al*., 2009; Cao *et al*., 2011; Zhao *et al*., 2012; Min and Lee, 2005).

Samples Partition: To perform the MLP analysis, data is split into three subsets: A training set to learn the network and adjust weight; a testing set to prevent overtraining and calibrate network; and an independent holdout set to assess the model (Min and Lee, 2005).

Based on the aforementioned materials, this study aimed to develop a recognition model in order to classify success of agricultural enterprises in Zanjan County in Iran.

MATERIALS AND METHODS

The objective of the study was achieved by measuring dependent variable, i.e. enterprise success, and independent variables, i.e. capitals owned by the enterprises, as well as developing a model to explain the relationship between them.

Dependent Variable

Success is a multi-criteria issue and is measured by some subjective and objective criteria. In this study, to create a composite success index, subjective and objective criteria (Table 1) weighted by experts and TOPSIS [TOPSIS method (Technique for Order of Preference by Similarity to Ideal Solution) is based on the idea that the best alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution.] method based on Li-Fang *et al*. (2012) and Zhu *et al*. (2013) were applied to score and classify the enterprises. Thus, success index is an ordinal variable with three levels of success (Class 1=low; Class 2= Medium, and Class 3= High).

Table 1. Criteria of enterprise success measurement.

Dimension	Criteria – (Measurement)	Dimension	Criteria – (Measurement)
Economic achievements	Inverse of ICOR - (ratio of additional outputs/values to new investment)	Social Achievements (Life quality)	Promotion of household consumption - (LS)
	Capital productivity - (Value added/ Total capital stock)		Promotion of self-reliance - (LS)
	Expanding of enterprise /business - (LS) [a]		Increasing of job satisfaction - (LS)
Environmental impacts	Impact on groundwater withdrawal - (LS)		Impact on household health - (LS)
	Impact on fertilizer using - (LS)	Social Achievements (Employment)	Increasing of worker numbers - (Worker)
	Impact on pesticide using - (LS)		Increasing of part time workers - (Day)
Social achievements (Empowerment)	Promotion of management abilities - (LS)		
	Promotion of technical abilities - (LS)		
	Promotion of marketing And Competition abilities - (LS)		

[a] Means the criterion has been measured by 5-point Likert Scale.

Independent Variables

Independent variables include *EnC, EC, HC* and *SC*. As Table 2 shows, these capitals consist of many items. To determine enterprise scores and form aggregated index for each quadruple capital, the separate items were free-scaled/standardized and then aggregated.

Architecture of the MLP

NN architecture was done with the aid of the SPSS software. Based on literature review guidance, architecture of the MLP has been carried out as follow: One input layer, one output layer, one hidden layer, 4 input layer nodes, 3 output layer nodes, and 6 hidden layer nodes(Identified by trial and error, considering CAR of holdout set as well as performance of testing and training sets). Batch updating approach with *SCG* was used for network training and weighting. Hyperbolic tangent activation function in hidden layer and sigmoid activation function in output layer was applied. Ninety two samples were split into 52 (56%) samples for training set, 20 (22%) samples for testing set, and 20 (22%) samples for holdout set. And, finally, *CAR* and Receiver Operating Characteristic (ROC) Curve was used to assess the model. At the end, sensitivity analysis, also known as independent variable importance analysis, based on (Liu *et al*., 2015; Wang *et al*., 2015) has been used to assess the relative importance of each independent variable in the modeling.

Location and Data Collection

This study was conducted in Zanjan Township located in Zanjan province, Islamic Republic of Iran. The majority of the data was gathered by using a structured questionnaire and having interviews with 92 agricultural production enterprise owners/farmers. They were selected based on some attributes including residence in the

Table 2. Criteria of enterprise capital measurement/explanatory factors.

Capital	Factors	Criteria– (Measurement)	Capital	Factors	Criteria- (Measurement)
EnC	Infrastructures	Access to information and communication technology - (LS)[a]	*HC*	Education	Formal education - (Years)
		Quality of roads and access to transportation vehicles - (LS)			Vocational education - (Number of extension courses)
		Easy access to energy (electricity, gasoline, gas) - (LS)		Experience	Business experiences - (Year)
		Enterprise distance from market - (Kilometer)		Skills	Level of technical skill - (LS)
	Natural resource	Easy access to basic resource (water) - (LS)			Level of management Skill - (LS)
		Suitability of natural resources (water and soil) - (LS)			Entrepreneurship Skill - (LS)
	Business services	Access to technical production advisors - (LS)	*SC*	Trust	degree of trust to farm workers - (LS)
		Access to marketing advisory services - (LS)			Rate of trust to institutes and rules - (LS)
		Access to a farming lawyer (if needed) - (LS)		Participation	Participation rate in village public works - (LS)
		Access to government supportive services - (LS)			Rate of mutual aids - (LS)
		Availability of production factors (workers and other inputs) - (LS)		Networking	Rate of contact with similar enterprise - (LS)
EC	Economic value of assets	Equipment and construction - (Monetary unit)			Rate of contact with agricultural institutes - (LS)
		Machinery - (Monetary unit)			Rate of contact with customers / providers - (LS)
		Land - (Monetary unit)			Membership in groups - (Yes, No)

[a] Means the criterion has been measured by 5- point Likert Scale.

village and holding subsidized loan from the Agricultural Bank of Islamic Republic of Iran in 2005-2010, and the loan had been invested to develop the enterprises in those years. Investment was defined as spending the loans on machinery and equipment such as electrifying irrigation wells, promoting irrigation technology, and land leveling.

Local experts believed that at least three years was required for stabilizing the outputs of the investment, therefore, the respondents were asked about the investment outputs in 2013, and all monetary values such as loans were adjusted to 2013 values using inflation rates. Further, it should be noted that a few questionnaires had some problems that were revised in 2014.

RESULTS AND DISCUSSION

According to literature review, success is a multidimensional issue. So, we considered environmental, social, and economic aspects to define and measure the success. Notably, success is affected by the content and availability of economic, human, social, and environmental capitals. Literature review also emphasized that NN models are appropriate techniques for prediction and classification issues and do not suffer from restrictive assumptions, thus, they are preferable to classical and traditional statistical methods such as Multiple Discriminant Analysis (MDA) and logistic regression. Therefore, a MLP with back propagation algorithm, a type of NN models, was applied in this study and its suitability was assessed by *CAR* criterion. A graphical depiction of the MLP architecture is given in Figure 1. The MLP consisting of one input layer with 4 nodes, one hidden layer with 6 nodes, and one output layer with 3 nodes. Hyperbolic tangent activation function in hidden layer and sigmoid activation function in output layer were applied to transfer signals from inputs to outputs.

CAR is used to assess the model. In this study, the *CAR* of holdout data was used to test the practical results of the network. The result shows that the model correctly classified 86.4% samples (Table 3). *CAR* indicated that the model appeared to perform well for “enterprises in Class 1” with CAR of 100%, but it did not do well for the enterprises which were in Class 2 (medium success) with CAR of 71.4%". Enterprises that experienced “high success (Class 3)” were put in the middle.

ROC curve was another output of MLP network application. The Area Under Curve (AUC) is used to assess the validity of the model. While *CAR* refers to the ratio and number of enterprises that are correctly classified, *AUC* refers to the probability that an enterprise lies in its actual class.

ROC curve is generally depicted in a square box. The diagonal line joining the point (0, 0) to (1, 1) divides the square box in two equal parts and each has an area equal to 0.5. The *AUC* is typically between 0.5 and 1. When *AUC* is close to 1, the model diagnostic power is increased, so, *AUC*= 1 means the accuracy is 100%. When *AUC* is close to 0.5, the model diagnostic power is decreased and, so, *AUC*= 0.5 indicates the model has no diagnostic power and prediction is done by chance. According to Greiner *et al.* (2000), an AUC has the following meanings: Non-informative (AUC= 0.5), less accurate (0.5< AUC=< 0.7), moderately accurate (0.7< AUC=< 0.9), highly accurate (0.9< AUC< 1) and perfect tests (AUC= 1). Results of this study reveals the AUC of Class 1, Class 2 and Class 3 are 0.94, 0.92, and 0.99, respectively. It means the model has categorized the enterprises in their actual classes with a high probability.

The other purpose of this study was investigation of importance of explanatory factors, which generally do not have the same importance in enterprise success and, as a consequence, in the model. It is, therefore, necessary to identify which of the input variables are most influential. Results, depicted in Table 4, show the model was dominated by the *HC*, followed by *SC* and, distantly, *EC* and *EnC*. Therefore, it is concluded that quality of individuals is a key factor to do a successful business in the farming. Also, it elicited that *SC* is the next important productive capital, is essential in input-output relationship and consequently affects agricultural enterprise success.

These arguments were challenged by Unger *et al.* (2011) who found a significant

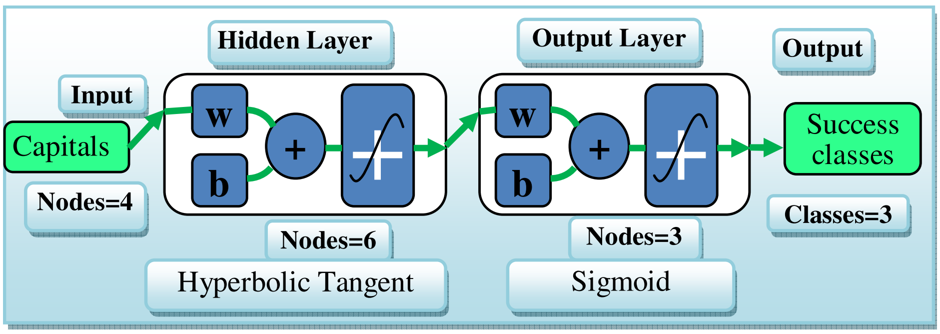

Figure 1. The MLP architecture applied for the classification.

Table 3. Classification of Accuracy Rate (CAR).

			Predicted			
			Success level			Predicted,
	Samples	Success level	Low	Medium	High	correctly
Observed	Training	Low	17	0	0	100.0%
		Medium	1	19	2	86.4%
		High	1	0	12	92.3%
		Overall percent	36.5%	36.5%	26.9%	92.3%
	Testing	Low	6	0	0	100.0%
		Medium	1	6	0	85.7%
		High	1	0	4	80.0%
		Overall percent	44.4%	33.3%	22.2%	88.9%
	Holdout	Low	7	0	0	100.0%
		Medium	2	5	0	71.4%
		High	0	1	7	87.5%
		Overall percent	40.9%	27.3%	31.8%	86.4%

Dependent variable: Success class.

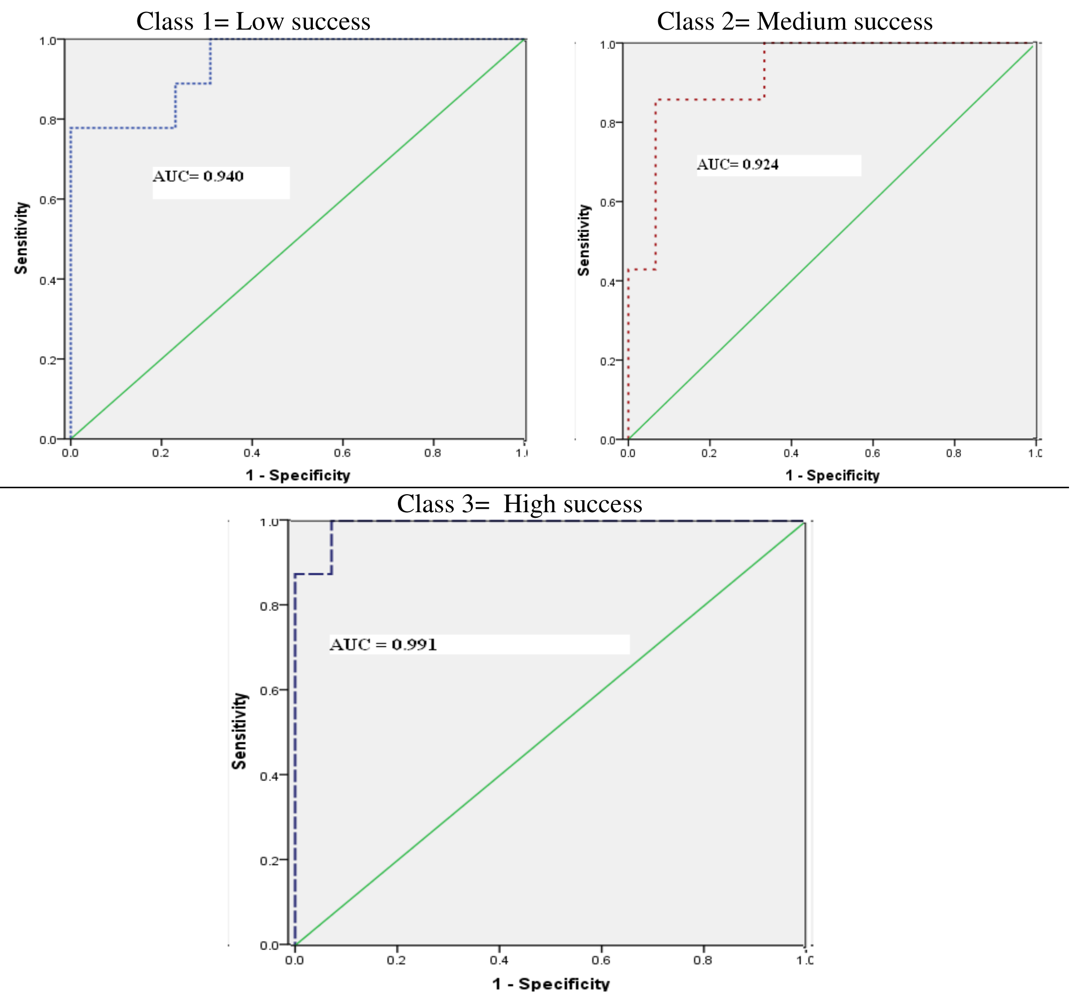

Figure 2. Receiver Operating Characteristic (ROC) Curve and the Area under Curve (AUC).

Table 4. Importance of explanatory factors.

Explanatory factors	Importance	Normalized importance
HC	.378	100.0%
SC	.287	75.7%
EnC	.124	32.8%
EC	.211	55.7%

relationship between *HC* and success. Guo *et al*. (2012) indicate that there is a positive correlation between *HC* and career success, and *HC* is an excellent predictor of career success. It is argued that the *HC* endowments facilitate physical capital investment, new technology adoption, information access (Martin *et al*., 2013). Entrepreneurs with high *HC* constitute an important means of gaining access to business information and advice (Anderson and Miller, 2003). Also, *HC* has indirect significant effect on sales growth through social capital (Nishantha and Kawamura, 2011). The magnitude of *HC* importance on success varies considerably across studies because of context, conceptualizations, and choice of success indicators (Unger *et al*., 2011). Some evidences (Anderson and Miller, 2003) indicate that the enterprises with high *HC* endowments can enter social networks, and gain more credit, advice, and business and market information.

In this study, we were interested in investigating which aspects of *HC* were more related to enterprise success. So, correlation analysis was applied to identify the relationship between success and *HC* aspects, including education, experiences, and skills. Results explored “entrepreneurial skill” and “management skill”, which are the factors most related to success, respectively. Also, investigation of the relationship between success and *SC* aspects shows that the “institution trust” had the most positive correlation with “enterprise success”. Besides, network sensitive analysis showed that *EnC* role in mapping network input-output was less than the other capitals. The data revealed that *EnC* score of most enterprises were close to each other and Coefficient of Variation (CV) was relatively less. Therefore, it could be interpreted that the low importance of *EnC* in input-output mapping was because of uniformity of the environmental capital for most enterprises in the study area. This issue, as a limitation for the model, can reduce model generalizability to regions with manifold *EnC*.

CONCLUSIONS

Difference in performances and, consequently, successes of agricultural enterprises were the basic motivation for conducting this study. So, this study aimed to develop a recognition model to predict and classify success of agricultural enterprises. Literature review revealed that success depends on supplementary capitals including Human Capital (HC), Social Capital (SC), Economic Capital (EC), and Environmental Capital (EnC), which are unevenly distributed in enterprises and rural areas. *EC* is fundamental to create a business. *EnC* plays a key role in encouraging or limiting performance. *HC* and *SC*, as intangible resource assets, are vital to the entrepreneurial process and foster survival, growth, and success of a business.

We also concluded that NN models can be more accurate and reliable for classification and prediction and MLP with back propagation algorithm, a type of NN models, is a preferable recognition model to explain the relationship between the capitals and the enterprise success and classifying the cases. So, within the present research’s scope, a MLP consisting of one input layer with 4 nodes, one hidden layer with 6 nodes, and one output layer with 3 nodes was applied. *CAR* and *ROC* curve applied for assessment and validation of the model. Based on *CAR* of the holdout data, the model was able to classify 86.4% of the samples correctly. In addition, based on *CAR*, the developed model is more suitable for predicting samples with “low success class” compared to the “medium” and “high success” classes.

Another indication derived from this study is that the four capitals have different roles in enterprise success and, as a sequence, in the model. The findings lead us to conclude that *HC* is the most important factor in the model. It implies that knowledge, skill, competency, and ability of the individuals significantly affect enterprise success. To promote enterprise success, *HC*, as the main capital, should be increased. Analysis of *HC* aspects revealed that “entrepreneurship skill” is relatively more related to enterprise success. In the next step, the model is affected by *SC* and followed by *EC* and *EnC*. Thus, to accelerate agricultural sector, tangible and intangible capital e.g. human, social, and economic capitals, should simultaneously be enhanced in rural areas.

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ارائه مدلی برای پیش بینی سطح موفقیت بنگاه‌های تولیدی کشاورزی بر اساس سرمایه های بنگاه‌ها

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چکیده

به منظور استفاده بهینه از منابع محدود در کشاورزی، تشخیص موفقیت و دسته بندی بنگاه‌های کشاورزی ضروری می‌باشد. این تحقیق قصد دارد با ارئه مدلی موفقیت بنگاه تولیدی را براساس متغیرهای پیش بین دسته بندی کند. متغیرهای پیش بین شامل سرمایه‌های محیطی، اقتصادی، اجتماعی و انسانی می‌باشد. متغیر وابسته «موفقیت بنگاه‌ها تولیدی» کشاورزی می‌باشد که براساس معیارهای ذهنی و عینی اندازه‌گیری و با استفاده از تکینک «شباهت به گزینه ایده‌ال» نمره دهی و به سه کلاس تقسیم شده است. بنابراین مسئله حاضر از نوع دسته‌بندی است و برای تبیین آن از شبکه عصبی استفاده شده است. این تحقیق در سال 1392-93در شهرستان زنجان انجام شده است. داده‌ها به وسیله پرسشنامه و از طریق مشاهده میدانی و مصاحبه با ۹۲ نفر از کشاورزان و یا صاحبان بنگاه تولیدی کشاورزی که بین سال‌های ۱۳۸۴ تا ۱۳۸۹ از بانک کشاورزی تسهیلاتی به منظور سرمایه گذاری دریافت کرده بودند، جمع‌آوری شده است. نتایج تحقیق نشان می‌دهد که بر اساس شاخص دقت دسته بندی، منحنی راک و میانگین مربعات خطا، شبکه عصبی چندلایه پرسپترون با یک لایه پنهان و ۶ نرون، مدل مناسبی است . ارزیابی مدل نشان می‌دهد که شبکه قادر است بطور متوسس ۴/۸۶ درصد از نمونه‌ها را به درستی دسته‌بندی کند. همچنین تحلیل اهمیت متغیرهای پیش بین حاکی از آن است که سرمایه انسانی،

اجتماعی، اقتصادی و محیطی به ترتیب بیشترین تا کمترین نقش را دارند. بنابراین به منظور افزایش عملکرد و موفقیت فعالیتهای تولیدی کشاورزی، ارتقای همزمان سرمایه های ملموس نظیر سرمایه اقتصادی و زیرساختها و سرمایه های غیرملموس نظیر سرمایه انسانی و اجتماعی ضروری بوده و می تواند بسیار موثر واقع شود.