Input Value Chain Affect Vietnamese Rice Yield: An Analytical Model Based on a Machine Learning Algorithm

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***Abstract*—Input value chains greatly affect rice yield, however previous related studies were mainly based on empirical survey and simple statistics, which lacked generality and flexibility. The article presents a new method to predict the influence of input value chain on rice yield in Vietnam based on a machine learning algorithm. Input value chain data is collected through field surveys in rice-growing households. We build a predictive model based on the neural network and swarm intelligence optimization algorithm. The prediction results show that our proposed method has an accuracy of 96%, higher than other traditional methods. This is the basis for management levels to have orientation on the input supply value chain for Vietnamese rice, contributing to the development of the Vietnamese rice brand in the world market.**

Keywords—Value chains; Vietnamese rice; machine learning; neural network

I. Introduction

A value chain is a sequence of activities in which the product passes through all the activities in order and at each activity, the product acquires some value [1]. Value chain development plays a very important role in the development of Vietnam's agriculture. The role of the value chain manifests itself in aspects such as promoting the improvement of productivity and quality of agricultural products, being a basic solution for product distribution and consumption, and increasing the attractiveness of investment in agriculture, etc. With underdeveloped agriculture in Vietnam, the role of the value chain is becoming more and more important. The effectiveness of the value chain depends on the cooperation of the members of the chain. When participating in cooperation in the value chain, members enjoy many benefits, especially the conditions to reduce costs, improve productivity and product quality, reduce sourcing time, be stable in production, etc. If participating in the global value chain, members also enjoy higher benefits, have conditions to increase productivity, improve product quality, have the opportunity to easily penetrate international markets, and increase profits, etc. In Vietnam, developing linkage cooperation along the value chain model is a condition for agricultural development. More than 75% of our agricultural products have to go through intermediaries or foreign brands to approach the international market. Therefore, many people combine to form a value chain, which will attract the participation of suppliers, distributors, and processing companies [2][3][4].

With favorable natural conditions, Vietnam has become a powerhouse in rice exports, just behind India and Thailand. According to UN FAO data, in 2017, Vietnam had more than 80 rice-exporting enterprises, accounting for about 20% of global rice exports [5]. However, because Vietnamese rice brands are not outstanding enough in the international market, although the export volume is high, it is mainly in the low and medium-quality segments. To overcome this problem and create sustainable development for the rice industry, the Vietnamese government is finalizing many drafts of the Regulation on the management of national certification marks for Vietnamese rice. Along with that, the development of stages in the rice value chain is also invested and interested. In the current Vietnamese rice industry, the value chain is mainly vertical. The main interlinked actors are input, production, conversion, distribution, and consumption. The input value chain is the opening stage and determines the output and productivity of Vietnamese rice [6][7]. Therefore, research to assess the impact of factors in the input value chain affecting Vietnamese rice is extremely necessary.

In recent years, along with the development of computers, artificial intelligence, and machine learning algorithms have been born that have solved countless problems of statistical analysis in economics that traditional analytical methods have not been able to achieve. Machine learning makes data processing, calculation, and analysis faster and more accurate, helping economic researchers' approach and evaluate hot issues [8][9][10]. Valendin et al. [11] used recurrent neural networks to analyze customers. They propose a new approach by using the history of individual customer transactions and relevant contextual factors to predict future behavior, and linking the characteristics of the individual and customer. This approach can help managers capture seasonal trends and buying dynamics. Chen et al. [12] designed a manufacturing enterprise environmental cost control system using the decision tree algorithm of machine learning. This method can realize the optimization of the circular economy value chain, and put forward important suggestions for the control of environmental cost schemes. Liu et al. [13] explored the application of artificial intelligence in global value chains. The results confirm that there is a significant positive correlation between artificial intelligence and the industry's global value chain. Liu et al. [14] established an economic risk prediction model using artificial intelligence algorithms based on the analysis of global value chains. This method can realize its trend prediction and provide an important theoretical reference for global value chain economic risks.

Traditional methods of studying the effects of value chains on products are mainly based on empirical surveys and simple statistics, which lack generality and flexibility, leading to many non-conforming conclusions, even imprecise. Therefore, applying intelligent assessment methods to value chain analysis is essential, it can solve some problems existing in traditional methods. This study proposes a new method of analyzing the input value chain affecting the yield of Vietnamese rice based on a machine learning method. First, we collect data through actual survey sources. Next, based on a new machine learning algorithm to build a predictive model, to improve the accuracy of the model, an optimization algorithm is applied to optimize the parameters. Finally, experiments to evaluate the effectiveness of the proposed model.

II. Method

A. Data Collection and Processing

In this study, data were collected from rice-growing households in the Mekong Delta of Vietnam including Kien Giang, Long An, An Giang, Dong Thap, and Soc Trang provinces. Information and data were collected through direct interviews with rice growers, soil quality statistics, and from input suppliers such as agricultural mechanical engineering companies, companies providing seeds and plant protection drugs. Data collection is based on trained collaborators and under the supervision of the research team. We use random sampling in combination with different geographic zoning, this combination will increase the generality for many regions. In addition, we conducted interviews with long-term rice growers and experts to assess, and gain practical experience and the current situation, thereby deepening our understanding of the actual situation in the data collection area. Finally, we selected input data to build predictive models including soil quality, water source, seed supply, fertilizer supply, agricultural medicine supply, science and technology, access to credit, age of homeowners, number of years in occupation, and qualification of homeowners.

Since the collected data is heterogeneous, it is necessary to normalize the data to enhance the training process of the model. In this paper, we use the method of max normalization to normalize the data [15], this method will select the largest number to return to 1, and the remaining numbers will be proportional to the range from 0 to 1.

B. Extreme Learning Machine

The training set has N samples $(\mathbf{x}_i, \mathbf{t}_i)$, $\mathbf{x}_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^T \in \mathbf{R}^n$, $\mathbf{t}_i = [t_{i1}, t_{i2}, \cdots, t_{im}]^T \in \mathbf{R}^m$, the mathematical expression of extreme learning machine (ELM) [16][17][18] is shown in Equation (1).

$$f_{ELM-L}(\mathrm{x}) = \sum_{j=1}^{L} \beta_j g(\mathbf{w}_j \cdot \mathbf{x}_i + b_j) = \mathbf{t}_i \,;\, b_j, \beta_j \in \mathbf{R} \quad (1)$$

here, $\mathbf{w}_j = [\mathrm{w}_{j1}, \mathrm{w}_{j2}, \cdots, \mathrm{w}_{jn}]^T \in \mathbf{R}^n$ is the input weight, L is the hidden layer nodes, b_j is the bias, β_j is the output weight, and $g(\bullet)$ is the activation function. Equation (1) and Equation (2) are the same.

$$\mathbf{H}_1 \beta_1 = \mathbf{T} \quad (2)$$

here,

$$\mathbf{H}_1(\mathbf{w}_1, \cdots, \mathbf{w}_L, b_1, \cdots, b_L, \mathbf{x}_1, \cdots, \mathbf{x}_N) = \begin{bmatrix} g(\mathbf{w}_1 \cdot \mathbf{x}_1 + b_1) & \cdots & g(\mathbf{w}_L \cdot \mathbf{x}_1 + b_L) \\ \vdots & & \vdots \\ g(\mathbf{w}_1 \cdot \mathbf{x}_N + b_1) & \cdots & g(\mathbf{w}_L \cdot \mathbf{x}_N + b_L) \end{bmatrix}_{N \times L} \quad (3)$$

$$\beta_1 = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m} \qquad \mathbf{T} = \begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_j^T \end{bmatrix}_{N \times m} \quad (4)$$

$\mathbf{T}$ is the actual value matrix.

The β_1 is calculated by the Equation (5).

$$\beta_1 = \mathbf{H}_1^{+} \mathbf{T} \quad (5)$$

here, $\mathbf{H}_1^{+}$ is the Moore Penrose matrix of $\mathbf{H}_1$.

C. Differential Squirrel Search

The differential squirrel search (DSS) method was presented in 2021 [19]. This approach combines the differential evolution and the squirrel search algorithm. Originally, the squirrel's position is determined at random. Its fitness is measured by the fitness function and is similar to the quality of the food supply found by the squirrel at that place. Then, the best position $\mathrm{PS}_{\mathrm{ht}}$ is in the fitness values. We record the three best position values $\mathrm{PS}_{\mathrm{at}}(1:3)$, the remaining locations $\mathrm{PS}_{\mathrm{nt}}(1:\mathrm{NP}-4)$ are believed to have yet to find any food sources. In the presence of a predator, squirrels shifted courses at random while foraging. Equation (6) depicts the revised locations of the squirrels on the acorn trees.

$$\mathrm{PS}_{\mathrm{at}}^{\mathrm{new}} = \begin{cases} \mathrm{PS}_{\mathrm{at}}^{\mathrm{old}} + \mathrm{d}_g \cdot G_c \left(\mathrm{PS}_{\mathrm{ht}}^{\mathrm{old}} - \mathrm{PS}_{\mathrm{at}}^{\mathrm{old}} - P_{\mathrm{avg}} \right), & r_1 \geq P_{\mathrm{dp}} \\ \textit{random position}, & \text{otherwise} \end{cases} \quad (6)$$

where d_g is the random gliding distance, P_{avg} is the average of all squirrels position, , P_{dp} is the predator presence probability, G_c is the gliding constant.

The authors use the crossover method to increase the diversity of squirrels and avoid entering local minima, and Eq. (7) depicts its mathematical model.

$$\mathrm{PS}_{at,j,j}^{cr} = \begin{cases} \mathrm{PS}_{at,i,j}^{new}, \text{ if } \left(rand_j \leq \mathrm{Cr} \right) \text{or } j = j_{rand} \\ \mathrm{PS}_{at,i,j}^{old}, \text{ if } \left(rand_j > \mathrm{Cr} \right) \text{or } j \neq j_{rand} \end{cases} \quad \begin{matrix} j = 1,2,3,...,D \\ i = 1,2,3,...,NP \end{matrix} \quad (7)$$

where $\mathrm{PS}_{at,i,j}^{new}$ and $\mathrm{PS}_{at,i,j}^{old}$ are new and old positions, NP is the population size, $\mathrm{PS}_{at,j,j}^{cr}$ is the positions of the squirrels after crossover operation, D is the dimension of the problem, $j_{rand} \in [1, \mathrm{D}]$ is a random value, $rand_j \in [0,1]$, and Cr=0.5.

The position of the squirrels in the normal trees is updated as shown in Eq. (8).

$$PS_{nt}^{new} = \begin{cases} PS_{nt}^{old} + d_g \cdot G_c\left(PS_{at}^{old} - PS_{nt}^{old}\right), & r_2 \geq P_{dp} \\ \text{random position,} & \text{otherwise} \end{cases} \tag{8}$$

where $r_2 \in [0,1]$ is a random number.

The new positions of the remaining squirrels are shown in Eq. (9).

$$PS_{nt}^{new} = \begin{cases} PS_{nt}^{old} + d_g . G_c\left(PS_{ht}^{old} - PS_{nt}^{old}\right), & r_3 \geq P_{dp} \\ \text{random position} & \text{ortherwise} \end{cases} \tag{9}$$

The Eq. (10) is the crossover algorithm.

$$PS_{nt,j,j}^{cr} = \begin{cases} PS_{nt,i,j}^{new}, \text{ if } \left(rand_j \leq \mathrm{Cr}\right) \text{ or } j = j_{rand} \\ PS_{nt,i,j}^{old}, \text{ if } \left(rand_j > \mathrm{Cr}\right) \text{or } j \neq j_{rand} \end{cases} \begin{matrix} j = 1,2,3,\ldots,D \\ i = 1,2,3,\ldots,NP \end{matrix} \tag{10}$$

The new positions of the squirrels in the hickory trees are updated by Eq. (11).

$$PS_{ht}^{new} = PS_{ht}^{old} + d_g \cdot G_c\left(PS_{ht}^{old} - PS_{at}^{avg}\right) \tag{11}$$

D. Propose an Algorithm based on ELM and DSS

ELM uses a random method to initialize the parameters of the input layer and the hidden layer, and calculates the output weight through the Moore Penrose matrix. Since it does not need to iteratively update parameters, the running time of the model is greatly reduced, and it is an efficient neural network algorithm. However, due to the way of random input parameters, it will bring algorithm uncertainty, and the model cannot be guaranteed to be in the optimal state. Therefore, the input parameters need to be optimized to improve the accuracy and stability of the model. DSS has been proved to be an efficient optimization algorithm. Therefore, this study uses DSS algorithm to optimize the input parameters of ELM, and proposes an algorithm called DSS-ELM. The optimization process of the algorithm is shown in Fig. 1.

Algorithm 1: DSS-ELM algorithm

Random initialization parameters

for i=1:Imax

  Calculate the PS_{at} by Eqs. (6,7)

  Calculate the PS_{nt} by Eqs. (8,9,10)

  Calculate the PS_{ht} by Eq. (11)

  Update parameters.

end for

Output optimized **w**, and b of the RFRA.

III. Result

Survey data includes 378 rice farmers, rice farms, and rice farming cooperatives. For rice farmers, the labor force is mainly family members. With rice farms, hired labor is the main source. Farmers still produce rice based on experience, and following habits, but most have had the support of local agricultural extension organizations in technical advice. However, focusing on convenience is still deeply rooted in households' awareness, and economic efficiency and productivity are not high. From there, it shows that individual rice-producing households still face many difficulties to increase rice productivity. With large-scale farms or cooperatives, the organization of production is quite modern with the application of many mechanized machines and basic technical staff.

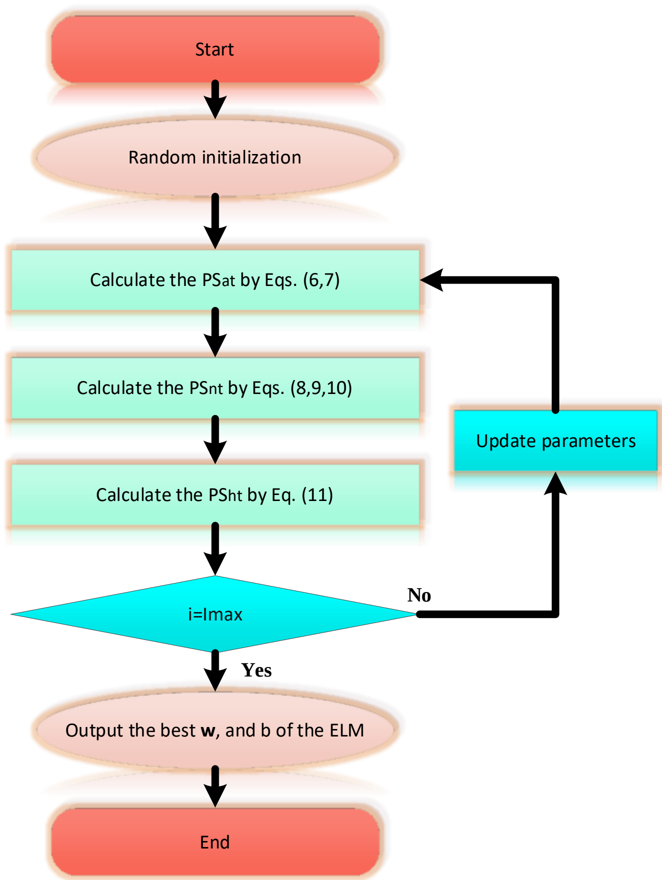

Fig. 1. DSS-ELM algorithm flowchart.

The data is divided into two classes. One class is the households that have achieved the desired yield after harvesting the rice and the other class is the households that have not achieved the desired yield. We randomly split it into a training set of 60% and a test set of 40%. Through the proposed algorithm, we build a training model to predict rice yield based on the input value chain. Fig. 2 shows the optimization process of the rice yield prediction model based on DSS-ELM. Here, we choose the number of iterations to be 100. We see that by the 15th iteration, the model has reached the maximum optimal level, the model converges quickly, and the error from 10% to 4%. Experimental results show that the DSS algorithm can optimize the model quickly, the model converges quickly and improves the classification ability. This result proves that DSS is an optimal algorithm with fast convergence speed, a good choice for parameter optimization problems. Using DSS to optimize the parameters of the ELM algorithm helps to improve the prediction accuracy of ELM. From there, it gives reliable results and serves as a reference for researchers or experts, and managers in the rice industry.

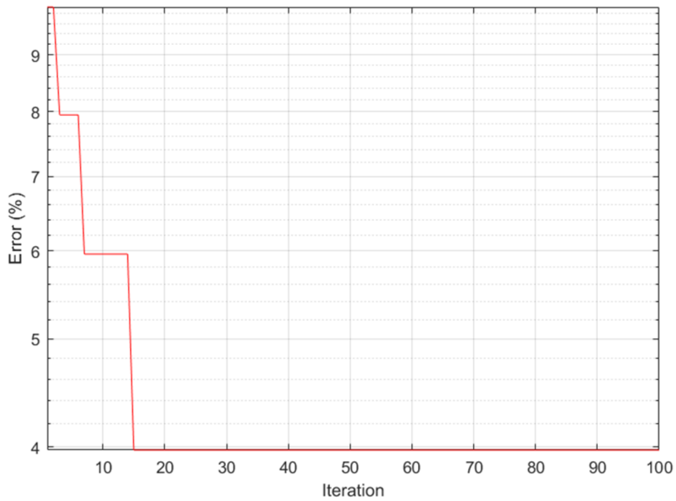

Fig. 2. Optimization process of DSS-ELM.

TABLE I. PREDICTION ACCURACY OF EACH CLASS

Class	Accuracy (%)
1	95.5
2	96.8
Overall	96.0

The two classes are labeled as 1 and 2. Table I is the accuracy of each class, the results show that the accuracy is high, with the accuracy of class 1 being 95.5%, and the accuracy of class 2 being 96.8% and the overall accuracy was 96%. Fig. 3 shows the difference between the samples of the two classes. We can see, the difference between the predicted number and the actual number is very small, only 6 out of 151 samples are wrong. From there, it shows that the model has good predictive results, and can predict well about rice yield based on input value chain data. This can be considered one of the important methods to support rice-growing households in choosing suitable inputs and orienting a particular rice-growing area. At the same time, it is also the basis for local authorities and managers to have specific orientations and directions to develop wet rice farming in Vietnam.

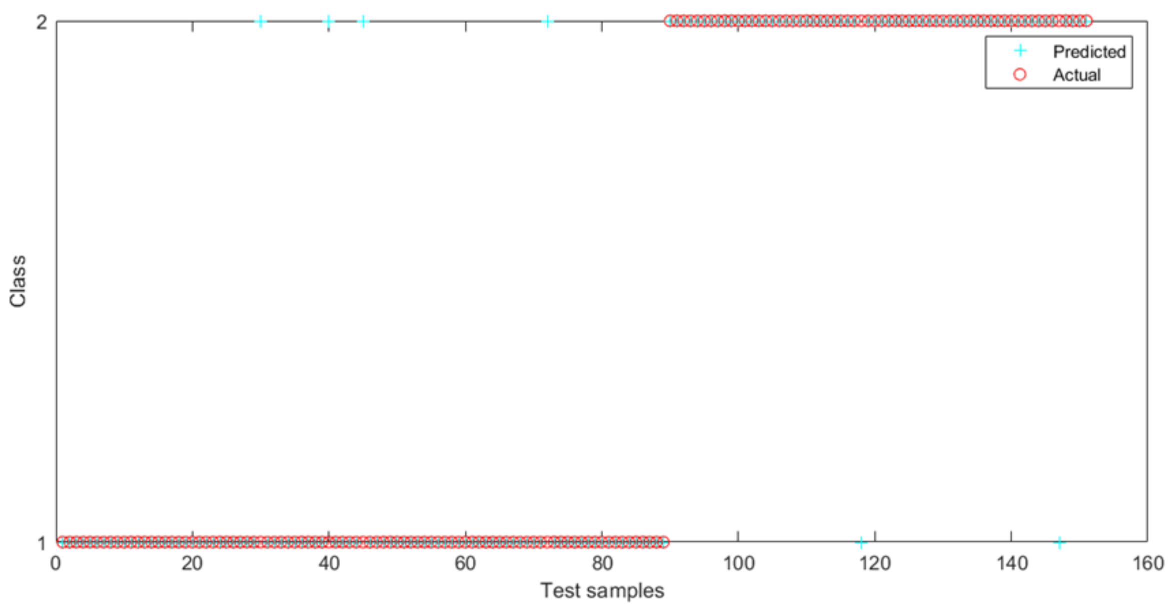

Fig. 3. Deviation between samples.

IV. DISCUSSION

A. *Key Characteristics of Input Value Chains affecting Rice Yield*

In this study, we take into account the characteristics affecting Vietnamese rice yield including soil quality, water source, seed supply, fertilizer supply, agricultural medicine supply, science and technology, access to credit, age of homeowners, number of years in occupation, and qualification of homeowners. The value chain of fertilizer supply, agricultural medicine supply, seed supply, and science and technology have a great influence on rice yield. They are also mentioned in studies around the world such as those of Amjath et al. [20], Darakeh et al. [21], and Katsu et al. [22].

For fertilizer supply, Vietnam is a country that actively produces fertilizers for agriculture, and becomes the main source of fertilizer for the rice industry. The main source of urea fertilizer supply is from enterprises such as Phu My fertilizer, Ca Mau protein, Ha Bac fertilizer, etc. The main source of phosphate fertilizer is the Lam Thao factory, and Long Thanh factory. In addition, there are a few enterprises producing and supplying organic and micro-organic fertilizers. However, the supply of fertilizer in Vietnam has not yet met the actual demand. According to recent statistics in three years, Vietnam imported 4.5 million tons of fertilizers of all kinds.

As for the supply of agro-pharmaceuticals, the market value of pesticides in Vietnam is about $900 million, and the growth rate is 6.8 %/year. There are more than 300 companies manufacturing and processing agro-pharmaceuticals in the whole country, but this number only meets 25% of the demand. The main supply comes from imports, and the supply from China accounts for 40% of the market share. Agro-pharmaceuticals are distributed through sales channels of enterprises and agents. The choice of agro-pharmaceuticals is usually based on self-drawing experiences and the introduction of neighboring households along with advertising information of agents. The capital for buying agricultural drugs is also limited, so it also greatly affects the yield of rice.

The supply of rice seeds is mainly through three main sources: farmers who self-seed, farmers who buy seeds from high-yielding fields, and farmers who buy seeds from seed centers. Farmers leave seeds for themselves, accounting for 10% of the number of seeds used, most of them are small production households, and do not accept large costs. Moreover, the seed dealers are quite difficult to reach. Seeds from high-yielding fields account for about 65%. The rest are people who buy seeds from seed centers across the country.

For technical-technological information sources, farmers associated with enterprises, enterprises are an important transfer channel in science and technology to rice growers through the regular organization of training sessions on the application of scientific and technical advances to production. For the remaining households, the source of access to science and technology mainly relies on pesticide companies, agricultural extension centers, and mass media.

B. Compare with other Models

Traditional methods commonly used to build models in economics include logistic regression (LR)[23], and support vector machine (SVM) [24][25]. In this study, we compare our proposed method with ELM, LR, and SVM methods. The comparison results are shown in Table II and Fig. 4. It can be seen that DSS-ELM has higher accuracy than other methods. Specifically, DSS-ELM is 6% higher than the ELM method, 4% higher than the SVM method, and 8.6% higher than the LR method. The LR and SVM algorithms use the Sigmoid function as a non-linear factor, thereby performing the classification problem. The ELM algorithm uses a neural network that simulates the human nervous system, through random weights and bias values, and then relies on the Moore-Penrose matrix to calculate the output weights. In this study, we use the swarm intelligence optimization method combined with the random parameters of ELM to conduct parameter optimization, thereby increasing the predictive ability of the algorithm. The results of the experiment proved that our proposal is accurate, and suitable for the problem of predicting rice yield in Vietnam based on the input value chain.

TABLE II. ACCURACY OF THE MODELS

Models	Overall accuracy (%)
LR	87.4
SVM	92.1
ELM	90.0
DSS-ELM (This study)	96.0

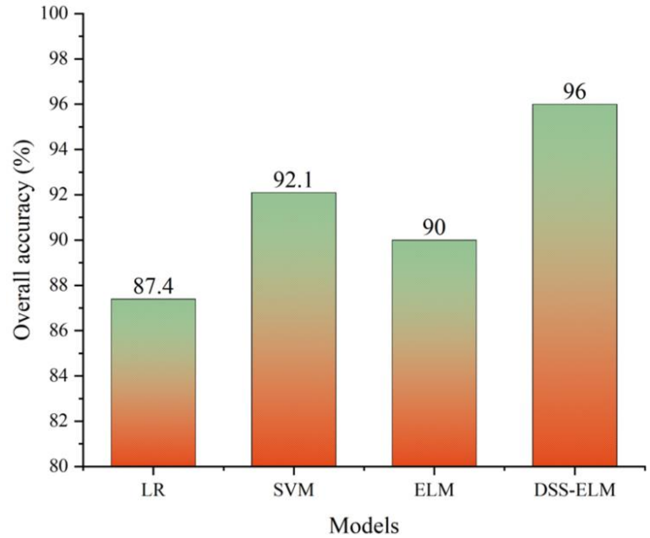

Fig. 4. Results of comparing the accuracy of the methods.

V. CONCLUSION

This study proposes a method to predict the effect of rice yield based on the input value chain and machine learning algorithm. The data surveyed by the research team from rice-growing households. The results show that the model has good predictive ability about the influence of the input value chain on rice yield. Our proposed method is also more accurate than methods such as ELM, SVM, and LR. This is the basis for management levels to have orientation on the input supply value chain for Vietnamese rice.

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