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Modeling the Growth State of Pleurotus Eryngii Stipe with Genetic Algorithm–Artificial Neural Network

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Abstract

In this paper, the artificial neural network (ANN) model was established to predict the growth state of *P. eryngii* in the culture process. Temperature, wind speed, carbon dioxide concentration and relative humidity were set to enter into the ANN, the length of the *P. eryngii* stipe were set to be the output. Using genetic algorithms (GA) to optimize the structure and learning parameters of ANN. The developed genetic algorithm-artificial neural network (GA-ANN) which include 8 and 4 neurons in the first and second hidden layers respectively, gives the lowest mean squared error (MSE). The correlation coefficient of predicted value and experiment value about *P. eryngii* stipe were 0.996 and 0.994, respectively. In addition, through sensitivity analysis it can be found that within a certain temperature range the impact of wind speed on the growth state of *P. eryngii* stipe is most obvious and following carbon dioxide concentration and relative humidity. The result showed that the developed GA-ANN model was suitable for predicting the growth state of *P. eryngii* stipe during the culture process.

Practical Applications: The growth of*P. eryngii* is a nonlinear process, which is affected by many factors. The main purpose of our study is to develop a model to predict the growth of *P. eryngii* stipe. It provided guidance for *P. eryngii* industrial production, reducing costs and increasing production.

Introduction

P. eryngii is commonly known as king oyster mushroom or king trumpet mushroom, highly valued for its superior texture, flavour and quality [1]. It is commonly cultivated in Europe, Middle East, and North America as well as in parts of Asia [2]. It is both rare medicinal and edible mushroom [3-5]. Modern pharmacological studies indicate that *P. eryngii* contain highly valued nutritional ingredients [6,7], as well as medicinal ingredients with medical activities including antioxidant [7-9]; cholesterol-lowering, cardiovascular diseases preventative [10-12] and antitumor activities [13-15]. Moreover, the polysaccharide of *P. eryngii* combined with bifidobacteria can not only improve the digestion function but also beautify human faces [16]. Therefore, *P. eryngii* are welcome to many consumers. However, in the process of cultivating *P. eryngii* under the influence of climate and geography, the output and quality are obviously unstable. In addition, the different culture conditions in the incubation room have a significant impact on the growth of *P. eryngii* stipe. And most companies have no scientific methods but only depend on experience to control cultivate conditions of the *P. eryngii*. In the process of production, we found that the culture conditions (temperature, wind speed, carbon dioxide concentration and relative humidity) of *P. eryngii* have a significant effect on the growth length of *P. eryngii* stipe. In order to reduce the production cost and raise production, the conditions of cultivating *P. eryngii* must be scientifically and reasonably controlled.

ANN has the capacity to handle the linear and nonlinear information automatically [17,18] and is composed of a large number of processing units. ANN is used to process information and store knowledge by simulating human brain [19]. But it does not truly portray human brain network, only to simplify and simulate the information and knowledge. At present, the ANN model as a mathematical tool has been widely used in chemistry, engineering, economic administration, transportation and other

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fields. For instance, [20] has applied recurrent neural networks and profiles method to predict furfural and 5-hydroxymethylfurfural content of fermented lotus root the [20]. And [21] has used ANN to assessment computational aesthetics of photos quality. Topuz used ANN to predict moisture content of some agricultural products such as hazelnut, bean and chickpea [22]. Panagou and Kodogiannis made use of neural networks to model microbial growth in food and animal feed [23]. However, the application of mathematical models based on ANN in predicting the growth length of *P. eryngii* is relatively fewer than in other processing fields.

Genetic algorithm is a new random search and optimization method developed rapidly in recent years, its basic idea is based on Mendel's genetics and Darwin's theory of evolution by natural selection and genetic mechanisms to search for the optimal solution. Genetic algorithm is characterized by self-organizing, self-adaption and intelligence [24,25]. Therefore, it can be used to solve complex and unstructured problems and effected by the corresponding fitness and objective function. Genetic algorithms attempt to find an appropriate algorithm to correct adverse conditions for optimizing the neural network. Based on the self-adaption of genetic algorithm, neural networks would be designed in order to obtain a satisfactory convergence and adaptability.

Due to the growth of *P. eryngii* is a nonlinear process and is affected by many factors. Therefore, the main purpose of this study is to develop a model to predict the growth length of *P. eryngii* stipe. It provided guidance for *P. eryngii* industrial production, reducing costs and increasing production.

Materials and Methods

Preparation of Spawn

Sawdust spawn was prepared by inoculating sawdust substrate consisting of sawdust and wheat at a 3:2 ratio with *P. eryngii* (Accc no.50894.) preserved in the microbiology laboratory in China Microbial Culture Collection. Culturing was performed at 22 °C until spawn running was apparent on the substrate.

Cultivation Methods

Substrate was prepared by mixing corn cobs, sawdust, bagasse, wheat bran, soybean meal, corn flour, lime, calcium hydroxide and water content with this proportion (30%, 20%, 20%, 16%, 8%, 4%, 1.15%, 0.85% and 64%, respectively). The prepared substrate was packed into polypropylene bags and the weight is 1.3 kg. Afterwards, they are sterilized and inoculated with 30 g of the sawdust spawn of P. eryngii. Culturing is carried out in an incubation room at 20 °C, until the polypropylene bags is full of mycelial after removal of the caps to enable fruit-bodies to emerge. At this time, the incubation room temperature was adjusted to 22 °C for another 4 d ~ 5 d. The next step is to deal with the mushrooms with two mushroom heads in each polypropylene bags. And then, the prepared polypropylene bags are respectively put into biochemical incubator which have five different gradient of temperature (7 °C, 12 °C, 17 °C, 22 °C)， wind speed (1 m/s, 2 m/s, 3 m/s, 4 m/s), concentrations of carbon dioxide (500 ppm, 1000ppm, 1500ppm, 2000ppm) and relative humidity (65%, 75%, 85%, 95%) are cultured until sampling. Triplicate *P. eryngii* are sampled.

Artificial Neural Networks

Multilayer artificial neural network consists of input layer, hidden layer and output layer [26]. The input layer is responsible for receiving information from the outside world, the output layer is responsible for the results of post-processing the output of the system, the hidden layer has a greater impact on the prediction accuracy of ANN model. Each neuron receives the information from the data processing of the previous layer, and neurons of each layer, have the same transfer function but each neuron is calculated independently. After calculation is completed, the results were passed to the next layer. Subsequently, the weights and thresholds are adjusted during the training process using gradient descent algorithm and the optimal number of iterations is determined by minimum average absolute error. Genetic algorithms is applied to optimize the artificial neural networks, which is an evolutionary algorithm and a method of searching in a simulated natural evolution process.

In this process, through genetic manipulation, selection, crossover and mutation are conducted to select fitness environment for the individuals of the population, optimizing generation to generation and the fittest surviving, until the optimal performance parameter set is selected. Before the start of the training, the back propagation neural network parameters of step length, momentum and the number of hidden layer are set as 0-1, 0-1 and 3-21 respectively [27]. The trained goal of genetic algorithms is to find minimum mean square error between experimental value and predictive value and make the performance of the neural network to achieve the best. In this study, 256 samples are divided into three parts randomly, 128 samples for train, 64 samples for cross and the last 64 groups as the new data to evaluate the performance of the artificial neural network model.

The topology of BP-neural network prediction model is a four-layer back propagation network. The input layer consists of four neurons (temperature, wind speed, carbon dioxide concentration and relative humidity) and the output layer contains two neurons (the length of A cm and B cm). But the number of hidden layer neurons is set by repeated training and experiment. Eventually the BP-neural network prediction model will obtain its best predicted performance when the number of the first and second hidden layers is 4 and 2, respectively. At this time the optimal iteration number is 15, and the MSE reaches the stable value of 0.0012. Until you get a satisfactory result before this process is the need to be repeated screening [28].

Statistical Treatment

P. eryngii samples grown well and strong are chosen to be cut open along the central axis. The pilei are removed remaining the stipes measured following. Experiments were performed in triplicates. Data were analyzed in OriginLaB-8s (OriginLab Corporation, USA). Mean values were determined for each case.

Results and Discussion

Bp- Artificial Neural Network

Based on repeated BP-artificial neural network testing and training of artificial neural network, the structural parameters were to achieve optimal. The predicted values of the length of *P. eryngii* stipe for training set obtained using the optimal architecture of the BP-artificial neural network and their corresponding experimental values are presented. The fitting curve of desired output and ANN output were shows that predicted values and experimental values have the very good fitting through the optimized BP-artificial neural network. Earlier, [29] used artificial neural networks to predict the antioxidant activity of tea. The results show that artificial neural network is a very effective tool for predicting the antioxidant activity of tea samples. Some researchers have also used ANN to predict the storage quality of green peppers. The results also show that the method has high fitting accuracy and is a very promising prediction method [30]. Some researchers have even used ANN to build prediction and classification models for wine and soy sauce [31,32]. Among these similar conclusions, it is not difficult to find that ANN is a very promising prediction tool.

Optimized Ann Model Performance Data Set

Currently there have been no uniform standard for the current set of relevant parameters specific ANN mathematical model [33], therefore, the use of ANN to predict the relevant parameters ANN mathematical model needs to repeat test and optimization. By repeated selection and experiments, the step, weights and the number of neurons is set, so that to achieve optimal ANN. A good mathematical model has a high R2 and a low MSE [34]. The predicting parameters of growth length of *P. eryngii* stipe are obtained by the optimized BP-ANN model. It can be seen that R2 of the prediction model for the A value and the B value are 0.9963 and 0.9947, respectively. Similarly, we obtained lower MSE values of 0.0736 and 0.1271, respectively.

Sensitivity Analysis

The purpose of analysis the sensitivity of artificial neural network is to investigate the relationship between the network input and output variables. The most important factors for growth length can be quickly and effectively screened out by the known input conditions. This analysis suggests that how to optimize different models from the known input variables [35]. Among four input factors temperature is the most important factors. In the previous study, it was also proved that temperature is the most important factor affecting the growth of *P. eryngii* [36-38]. In these four input variables of temperature, wind speed, carbon dioxide concentration and relative humidity, the growth length of *P. eryngii* stipe is the most sensitive to temperature and following wind speed, carbon dioxide concentration and relative humidity.

Conclusion

The above study indicates that artificial neural network has proven to be a powerful tool in learning the relations between the culture conditions as input and the *P. eryngii* stipe length as output. Therefore, it is possible to use BP-based artificial neural network to design better culture environment of growth of the *P. eryngii* stipe. It provides guidance for increasing the production of *P. eryngii* and saving costs of culture process.

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References

1. Zhang RY, Hu DD, Zhang YY, Goodwin PH, Huang CY, et al. (2016) Anoxia and anaerobic respiration are involved in “spawn-burning” syndrome for edible mushroom Pleurotus eryngii grown at high temperatures. Scientia horticulturae 199: 75-80.
2. Kim MK, Ryu JS, Lee YH, Kim HR (2013) Breeding of a long shelf-life strain for commercial cultivation by mono-mono crossing in Pleurotus eryngii. Scientia horticulturae 162: 265-270.
3. Li X, Wang L (2016) Effect of extraction method on structure and antioxidant activity of Hohenbuehelia serotina polysaccharides. International journal of biological macromolecules 83: 270-276.
4. Chen J, Yong Y, Xing M, Gu Y, Zhang Z, et al. (2013) Characterization of polysaccharides with marked inhibitory effect on lipid accumulation in Pleurotus eryngii. Carbohydrate polymers 97(2): 604-613.
5. Yang Z, Xu J, Fu Q, Fu X, Shu T, et al. (2013) Antitumor activity of a polysaccharide from Pleurotus eryngii on mice bearing renal cancer. Carbohydrate polymers 95(2): 615-620.
6. Li S, Shah NP (2015) Effects of Pleurotus eryngii polysaccharides on bacterial growth, texture properties, proteolytic capacity, and angiotensin-I-converting enzyme-inhibitory activities of fermented milk. Journal of dairy science 98(5): 2949-2961.
7. Lau BF, Abdullah N, Aminudin N (2013) Chemical composition of the tiger’s milk mushroom, Lignosus rhinocerotis (Cooke) Ryvarden, from different developmental stages. Journal of agricultural and food chemistry 61(20): 4890-4897.
8. Stajic M, Vukojevic J, Knezevic A, Duletic Lausevic S, Milovanovic I (2013) Antioxidant protective effects of mushroom metabolites. Current topics in medicinal chemistry 13(21): 2660-2676.
9. Ferreira IC, Barros L, Abreu R (2009) Antioxidants in wild mushrooms. Current Medicinal Chemistry 16(12): 1543-1560.
10. Berger A, Rein D, Kratky E, Monnard I, Hajjaj H, et al. (2004) Cholesterol-lowering properties of Ganoderma lucidum in vitro, ex vivo, and in hamsters and minipigs. Lipids in health and disease 3(1): 2.

11. Guillamón E, García Lafuente A, Lozano M, Rostagno MA, Villares A, et al. (2010) Edible mushrooms: role in the prevention of cardiovascular diseases. Fitoterapia 81(7): 715-723.

12. Sato M, Tokuji Y, Yoneyama S, Fujii Akiyama K, Kinoshita M, et al. (2013) Effect of dietary maitake (Grifola frondosa) mushrooms on plasma cholesterol and hepatic gene expression in cholesterol-fed mice. Journal of oleo science 62(12): 1049-1058.

13. Ren L, Perera C, Hemar Y (2012) Antitumor activity of mushroom polysaccharides: a review. Food & function 3(11): 1118-1130.

14. Fontana S, Flugy A, Schillaci O, Cannizzaro A, Gargano ML, et al. (2014) In vitro antitumor effects of the cold-water extracts of Mediterranean species of genus Pleurotus (higher Basidiomycetes) on human colon cancer cells. International journal of medicinal mushrooms 16(1): 49-63.

15. Xu L, Xu N, Zhu X, Zhu Y, Hu Y, et al. (2014) Modeling of Furfural and 5-Hydroxymethylfurfural Content of Fermented Lotus Root: Artificial Neural Networks and a Genetic Algorithm Approach. International journal of food engineering 10(4): 757-766.

16. Hwang YJ, Nam HK, Chang MJ, Kim SH, Noh GW (2005) Effect of Lentinus edodes and Pleurotus eryngii extracts on proliferation and apoptosis in human colon cancer cell lines (2003). Journal of the Korean Society of Food Science and Nutrition 32(2): 217-222.

17. Chithra S, Kumar SS, Chinnaraju K, Ashmita FA (2016) A comparative study on the compressive strength prediction models for High Performance Concrete containing nano silica and copper slag using regression analysis and Artificial Neural Networks. Construction and Building Materials 114: 528-535.

18. Dehghani AA, Mohammadi ZB, Maghsoudlou Y, Mahoonak AS (2012) Intelligent estimation of the canola oil stability using artificial neural networks. Food and bioprocess technology 5(2): 533-540.

19. Ziaei Rad M, Saeedan M, Afshari E (2016) Simulation and prediction of MHD dissipative nanofluid flow on a permeable stretching surface using artificial neural network. Applied Thermal Engineering 99: 373-382.

20. Xu B, Li C, Sung C (2014) Telomerase inhibitory effects of medicinal mushrooms and lichens, and their anticancer activity. International journal of medicinal mushrooms 16(1): 17-28.

21. Tan Y, Zhou Y, Li G Huang A (2016) Computational aesthetics of photos quality assessment based on improved artificial neural network combined with an autoencoder technique. Neurocomputing 188: 50-62.

22. Topuz A (2010) Predicting moisture content of agricultural products using artificial neural network. Advances in Engineering Software 41(3): 464-470.

23. Panagou EZ, Kodogiannis VS (2009) Application of neural networks as a non-linear modelling technique in food mycology. Expert Systems with Applications 36(1): 121-131.

24. Pawlak J, Hercman H (2016) Numerical correlation of speleothem stable isotope records using a genetic algorithm. Quaternary Geochronology 33: 1-12.

25. Kundakcı N, Kulak O (2016) Hybrid genetic algorithms for minimizing makespan in dynamic job shop scheduling problem. Computers & Industrial Engineering 96: 31-51.

26. Mallela UK, Upadhyay A (2016) Buckling load prediction of laminated composite stiffened panels subjected to in-plane shear using artificial neural networks. Thin-Walled Structures 102: 158-164.

27. Datta AK, Sablani SS, Mujumdar AS, Rahman MS (2006) Handbook of food and bioprocess modeling techniques. CRC Press.

28. Shankar TJ, Sokhansanj S, Bandyopadhyay S, Bawa AS (2010) A case study on optimization of biomass flow during single-screw extrusion cooking using genetic algorithm (GA) and response surface method (RSM). Food and Bioprocess Technology 3(4): 498-510.

29. Cimpoiu C, Cristea VM, Hosu A, Sandru M, Seserman L (2011) Antioxidant activity prediction and classification of some teas using artificial neural networks. Food Chemistry 127(3): 1323-1328.

30. Meng X, Zhang M, Adhikari B (2012) Prediction of storage quality of fresh-cut green peppers using artificial neural network. International journal of food science & technology 47(8): 1586-1592.

31. Ceballos Magaña SG, de Pablos F, Jurado JM, Martín MJ, Alcázar Á, et al. (2013) Characterisation of tequila according to their major volatile composition using multilayer perceptron neural networks. Food chemistry 136(3-4): 1309-1315.

32. Llzuka K, Aishima T (1997) Soy sauce classification by geographic region based on NIR spectra and chemometrics pattern recognition. Journal of food science 62(1): 101-104.

33. Majdi A, Beiki M (2010) Evolving neural network using a genetic algorithm for predicting the deformation modulus of rock masses. International Journal of Rock Mechanics and Mining Sciences 47(2): 246-253.

34. Kruzlicova D, Mocak J, Balla B, Petka J, Farkova M, et al. (2009) Classification of Slovak white wines using artificial neural networks and discriminant techniques. Food Chemistry 112(4): 1046-1052.

35. Yadollahi A, Nazemi E, Zolfaghari A, Ajorloo AM (2016) Application of artificial neural network for predicting the optimal mixture of radiation shielding concrete. Progress in Nuclear Energy 89: 69-77.

36. Cai A, Xiao J, Zhen Q, Ke Y, Fang B, et al. (2009) Effects of temperature and pH on mycelial growth of pleurotus eryngii. Agricultural science hubei (7): 1670-1673.

37. Gong Z, Yu S, Qu L (2002) Effects of nutrition and environmental conditions on mycelial growth of pleurotus eryngii. Journal of edible fungi 9(3): 13-17.

38. Li C (2014) Screening of different medium formulations for the production of Pleurotus eryngii. Northern Horticulture (3): 141-143.

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