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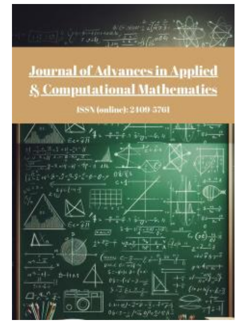

Enhancing Fruit Tree Yield Prediction with an Optimized Grey Neural Network Model Using the Fruit Fly Algorithm

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ABSTRACT

This article first integrates data on fruit tree yield and related influencing factors in Fujian Province, covering two major categories of factors: social and natural. On this basis, this article calculated the correlation coefficients between fruit tree yield and various factors, verifying the rationality of indicator selection. Subsequently, this article used a combination of grey model GM (1,1), BP neural network model, and fruit fly algorithm to optimize the grey model and neural network for fruit tree yield prediction. In the end, based on the research results, it was found that the combination model of fruit fly algorithm optimized grey model and neural network has a better prediction effect on fruit tree yield, which is more suitable for us to deeply understand the changes in fruit tree yield. It can also be well trained for relatively random natural factors.

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1. Introduction

The fruit industry has become the third largest agricultural planting industry in China [1], second only to grain and vegetables. However, with the changes in social and natural environments, the contradiction between market supply and demand has become increasingly prominent, resulting in some fruits being overstocked and unsold, and the overall price being relatively high but with insufficient added value. Therefore, through accurate prediction of fruit tree production, it can better adjust the supply and demand of the market, which has important practical significance. There are many methods for predicting fruit tree production, and the selection of indicators is also very diverse. Common prediction methods [2] include scenario analysis, regression analysis, exponential smoothing, grey model, BP neural network, etc. Common indicators selected include soil moisture, soil nutrients, soil pH value, tree species, leaf area index, fertilizer application amount, irrigation amount, etc. Hu Haijun [3] explored the impact of management indicators on apple tree yield, and summarized scientific methods by establishing predictive models. By reasonably utilizing water resources and fertilizers, accurate supply and management of apple tree production factors can be achieved; He Shulin *et al*. [4] used neural network algorithms to predict the water demand of fruit trees and achieved precise irrigation, accurately predicting the yield of fruit trees; Xiang Yanan [5] explored the relationship between industrial factors and fruit tree yield through methods such as grey correlation analysis and GM (1,1) prediction model, and accurately predicted fruit tree yield; Anderson Pedro Bernardina Batista *et al*. [6] investigated the impact of forest type on fruit tree yield and analyzed that under certain conditions, the fruit yield of one tree in a forest type can affect the fruit yield of adjacent trees.

Research on fruit tree yield at home and abroad mainly focuses on individual fruit tree varieties, traits, management conditions, etc. Although some progress has been made, there is still a certain gap between simulation experiments and reality. In real life, some difficult to predict natural disasters may occur, which will also affect fruit tree yield. In addition, how to improve prediction accuracy is still a key issue in research.

In response to the above shortcomings, this study will adopt a combination model of fruit fly optimized grey neural network [7] to apply to fruit tree yield prediction, and introduce natural factors with special characteristics (natural disasters, generally considered as low probability events) as impact indicators. The main goal is to approach reality in simulation experiments, consider extreme weather conditions, and strive to improve the accuracy of predictions.

This study is based on Fujian Province. Due to the frequent occurrence of climate disasters such as typhoons and heavy rainfall in the Fujian region, a series of sudden events such as geological disasters may occur [8], which may also affect fruit tree yields. Firstly, a comprehensive analysis was conducted on the selection of indicators in existing relevant research, combined with the factors of natural disasters and the availability of data. Eight data indicators were selected, which were divided into two categories: social factors and natural factors; Secondly, prove the rationality of selecting the constructed index and calculate the correlation coefficient between fruit tree yield and its influencing factors [9]; Finally, the constructed fruit fly algorithm is used to optimize the grey neural network model for predicting fruit tree yield, and accuracy comparisons are made with other models. For many other references, we can see [10-48].

2. Basic Theory

2.1. GM (1,1) Model

The Grey Prediction Model (GM) [49] is a model that uses discrete random numbers to establish differential equation forms. It performs well in predicting trend changes and only requires a small number of samples, but cannot approximate complex nonlinear functions. Some factors that affect fruit tree yield are non dynamic and non synchronous, which affects the accuracy of model predictions.

Steps for establishing a GM (1,1) grey prediction model:

1) Data testing

The original data column is called $\lambda(k)$:$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$, and the original data sequence is accumulated to obtain the accumulated sequence. Calculate:

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, k = 2,3,\ldots,n \tag{1}$$

If all $X = (e^{\frac{-2}{n+1}}, e^{\frac{2}{n+1}})$ sequences are $\lambda(k)$ in the middle, a GM (1,1) model can be established by X and we can use it for prediction.

2) Establish GM (1,1) model

If the $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ above criteria are met, a GM (1,1) model can be established and used as the data set.

$$x^{(0)}(k) + \alpha z^{(1)}(k) = b \tag{2}$$

$$\frac{dx^{(1)}(t)}{dt} + \alpha x^{(1)}(t) = b \tag{3}$$

Calculate a, b, obtain formula (4), and solve for the predicted value of the model.

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}k = 1,2,\ldots,n-1 \tag{4}$$

Using the analytical expression of the model, predict the accumulated sequence, and then use the reverse accumulation operation of the accumulated sequence to obtain the predicted value of the original sequence.

3) Test predicted value

Residual test: calculating relative residuals

$$\varepsilon(k) = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}, k = 1,2,\ldots,n \tag{5}$$

2.2. BP Neural Network Model

BP neural network [50] is a typical multi-layer feedforward neural network that can approximate any random function and performs well in handling nonlinear and complex predictions. However, excessive approximation may reduce generalization ability and affect model accuracy.

The specific operation process of BP neural network includes:

1) Parameter Allocation

Each input vector corresponds to an output vector, which is (X, Y) composed of a dataset. The number of input layer nodes in the network determines the dimensionality of the input layer$n$, and similarly, the number of output layer nodes determines the dimensionality of the output layer$m$.

2) The formula for calculating the data of hidden layer neurons is $H_f$as follows:

$$H_f = f(\sum_{i=1}^{n}(w_{ij}x_i - a_j)), j = 1,2,\ldots,L \tag{6}$$

$f()$ Represents the activation function, x_{ij}represents the weights of the input layer and hidden layer, and $b$represents the output layer threshold.

3) O_k The formula for calculating the data of output layer neurons is:

$$O_k = \sum_{i=1}^{L} H_i w_{ik} - b_k, k = 1,2,\ldots,n \tag{7}$$

H_i Represents the data in the hidden layer neurons, w_{jk}represents the weight from the hidden layer to the output layer, and $b$represents the output layer threshold.

4) Calculation error

The error of the network loss function is $e_k$expressed as:

$$e_k = Y_k - O_k, k = 1,2,\ldots,m \tag{8}$$

5) Update weights and thresholds

The error of the network loss function $e_k$can be optimized by updating the weights, which is known as the gradient descent method.

6) Predictive data

After the iteration of the model algorithm is completed, the prediction model is considered to have been successfully constructed, and the actual data can be substituted into the prediction model.

3. Establishment of a Combination Model for Optimizing Grey Neural Network with Drosophila Algorithm

Although BP neural networks require sufficient training samples and hidden nodes to approximate any function, grey system modeling prediction only requires a small number of samples, and BP neural networks usually use monotonically increasing sigmoid functions as excitation functions. Therefore, these two models have complementarity when dealing with complex nonlinear situations. However, the simple linear weighted combination method did not fully utilize the advantages of the two models. Therefore, this study explores the combination of the fruit fly algorithm and grey neural network to achieve better prediction results.

The specific steps for optimizing GNNM using the FOA algorithm are as follows:

Step 1: Firstly, attempt to preprocess the data related to the predicted event to determine whether the data is suitable for the grey neural model. If the data meets the requirements for model applicability, further normalization, ashing, etc. will be carried out on the data. As the common Min Max normalization method was first used in the normalization process of the data in this study, but the normalized data is not within the expected range, the Z-score normalization method is used to scale the data to a range of mean 0 and standard deviation 1, which is more suitable for the data in this article. Establish corresponding grey neural network models;

Step 2: Initialize the relevant parameters of the FOA algorithm, including maxgen and NP. The initial population of fruit flies emerged in this way;

Step 3: The process of olfactory search. Set the initial iteration number$(g = 0)$, motion direction, and random step size of the algorithm;

Step 4: Set the initial optimal taste concentration to infinity and determine the judgment value of taste concentrationS_i. According toS_i, calculate the odor concentration value of fruit flies, which is the adaptation value$Smell_i$, and use the error between the actual output value and the determined judgment value Eas the adaptation judgment function;

Step 5: Visual positioning process. This process involves selecting the individual with the highest fitness value as the optimal individual. Drosophila begins the visual search phase, flying towards the position of the optimal individual;

Step 6: Update iterative optimization to determine if the current adaptation value is the maximum value. If so, use the output parameters a and b to determine the structure, weight, and threshold of GNNM. Otherwise, repeat the above steps.

4. Combination Model Applications

4.1. Overview of the Research Area

This article takes the situation of fruit trees in Fujian Province as the research object, selects 8 data indicators, and divides them into two categories: social factors and natural factors. Social factors include fruit tree area (thousand hectares), total power of agricultural machinery (ten thousand kilowatts), and local financial expenditure decisions on land, resources, and meteorology (one hundred million yuan). Among them, local financial expenditure decisions on land, resources, and meteorology include local financial investment in agriculture and investment in geological disaster prevention; Natural factors include the affected area of floods (in thousands of hectares), drought (in thousands of hectares), wind and hail (in thousands of hectares), freezing (in thousands of hectares), and the number of geological disasters that occur. Among them, geological disasters include ground collapse, debris flow, collapse, and landslide. All influencing factors are from the website of the National Bureau of Statistics, with a time span of 2015-2022.

4.2. Data Preprocessing

The data used in this article is as follows (Table **1**). Some natural disaster data appears blank when collected on the official website of the National Bureau of Statistics, and this article assigns it a value of 0:

Based on the data from 2015 to 2022, perform dimensionless processing on it, and use the grey correlation analysis method to calculate the correlation coefficient between the grey correlation degree and the prediction index. The calculation formula is:

$$\xi(i,j) = \frac{min\left|x^{(0)}(i) - x^{(0)}(j)\right| + \rho \cdot max\left|x^{(0)}(i) - x^{(0)}(j)\right|}{|x^{(0)}(i) - x^{(0)}(j)| + \rho \cdot max|x^{(0)}(i) - x^{(0)}(j)|}$$

Where $x^{(0)}(i)$ and $x^{(0)}(j)$ represent the ith and jth raw data ρ, respectively, and are the resolution coefficients, which are taken in this paper$\rho = 0.5$. Perform weighted processing based on the calculated correlation degree.

It can be clearly seen from the calculation results that the correlation between fruit tree area and fruit tree yield is the highest, indicating that the planting area of fruit trees has the most significant impact on yield (Table **2**). Secondly, the number of decisions on expenditure on local finance, land resources, meteorology, and other affairs is also an important influencing factor. The correlation between the affected area of frozen disasters is the lowest, which is consistent with the subtropical monsoon climate characteristics of Fujian Province. Fujian Province has high temperatures and rainfall in summer, mild and humid winters, and less extreme low temperatures. Therefore, the impact of freezing disasters on yield is relatively small. These results are consistent with the actual situation, verifying the rationality of the selected indicators and the accuracy of the prediction model.

Table 1: Data.

	Area of Fruit Trees (Thousand Hectares)	Total Power of Agricultural Machinery (10000 Kilowatts)	Decision on Expenditure on Local Finance, Land Resources, Meteorology and other Affairs (in Billions of Yuan)	Flood Affected Area (Thousand Hectares)	Drought Affected Area (Thousand Hectares)
2015年	324.94	1384.13	33.43	76.8	0
2016年	304.52	1269.09	40.04	50.0	0
2017年	310.45	1232.42	48.60	12.8	20
2018年	331.79	1228.27	54.33	7.6	23.9
2019年	344.08	1237.73	53.57	93.6	21.6
2020年	355.78	1260.20	59.30	16.1	31.1
2021年	368.36	1270.52	52.80	23.1	1.3
2022年	377.09	1296.71	63.50	60.4	26.1

	Affected Area of Wind and Hail Disasters (Thousand Hectares)	Freezing Disaster Affected Area (Thousand Hectares)	Number of Geological Disasters Occurring (Times)	Fruit Production (10000 tons)
2015年	0.2	0	225	600.98
2016年	1.5	155.9	1327	591.76
2017年	0.1	0	82	644.67
2018年	0.8	10.5	29	683.11
2019年	7.9	0	163	727.21
2020年	3.6	0	27	764.58
2021年	1.9	13.7	35	810.29
2022年	5.3	14.1	202	864.94

Table 2: Grey correlation degree between fruit tree yield and its influencing factors.

Correlation result	Evaluation items	Area of fruit trees (thousand hectares)	Decision on expenditure on local finance, land resources,	Total power of agricultural machinery (10000 kilowatts)	Flood affected area (thousand he	Drought affected area (thousand hectares)	Affected area of wind and hail disasters (thousand hectares)	Number of geological disasters occurring (times)	Freezing disaster affected area (thousand hectares)
	Relevance	0.984	0.973	0.962	0.814	0.809	0.804	0.776	0.726
	ranking	1	2	3	4	5	6	7	8

Perform a rank ratio test on the original data sequence. This article uses rank ratios to test the data, as shown below (Table **3**):

From the above analysis shown in Table **3**, it can be concluded that all the level ratios of the original sequence are within the interval (0.801, 1.249), indicating that the original sequence is suitable for constructing a grey prediction model.

Table 3: Results of level comparison test.

Original Value	Grade Ratio
600.98	-
591.76	1.016
644.67	0.918
683.11	0.944
727.21	0.939
764.58	0.951
810.29	0.944
864.94	0.937

4.3. Analysis of Model Application Results

According to the previous text, the construction process of FOA-GNNM was detailed, and the prediction process is based on processed data and step input models. The algorithm for optimizing the parameters of the grey neural network using the fruit fly optimization algorithm was used to train and predict the data in this article. The optimization process is as follows (Fig. **1**):

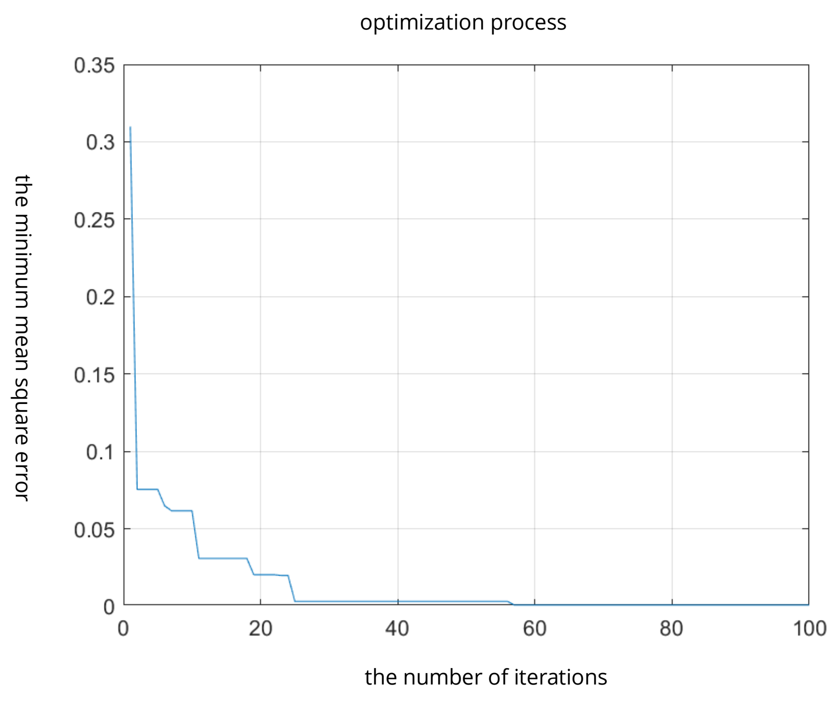

Figure 1: Optimization process diagram.

It can be seen that as the number of iterations increases, the minimum mean square error decreases, greatly improving the prediction accuracy of the model. In addition, this article also presents the movement diagram of fruit flies (Fig. **2**).

Comparing the predictive performance of traditional grey model, BP neural network model, and fruit fly algorithm optimized grey neural network combination model (Table **4**).

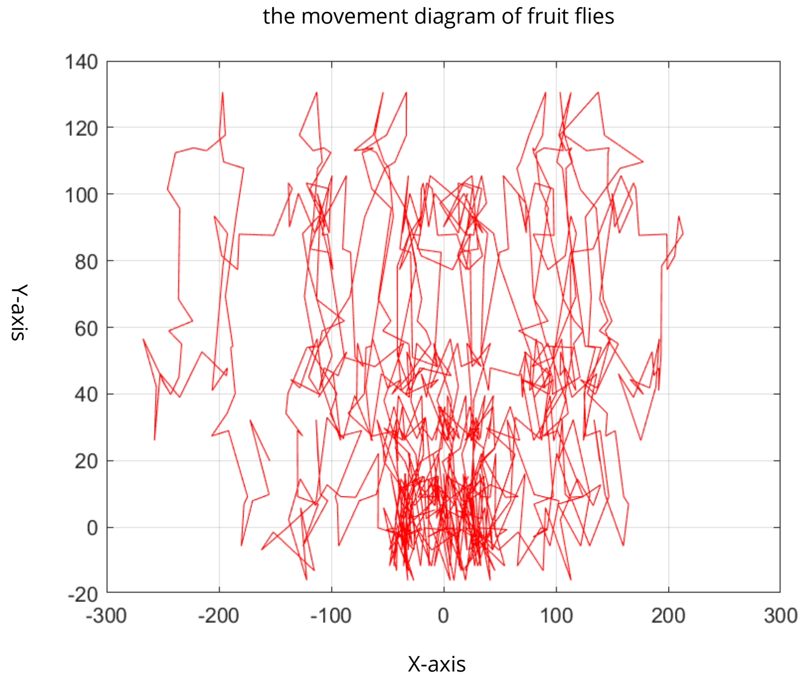

Figure 2: Drosophila flight route map.

Table 4: Model comparison.

	GM (1,1)	BP Neural Network	FOA-GNNM
Average absolute error (%)	1.075	1.100	0.076

By comparing the prediction results of the three models, it can be concluded that the improved combination model based on the fruit fly algorithm has the smallest average relative error and the highest prediction accuracy.

This indicates that the combination model of fruit fly algorithm optimized grey neural network can make correct predictions based on special natural disasters (generally considered as low probability events), and can be applied to processing small samples of data with special influencing factors, while also achieving good results. Therefore, this method is not only more scientific, but also combined with current policies for indicator selection, with comprehensiveness, dynamism, and timeliness. The predicted trend is in line with the actual trend of fruit tree yield changes. And it has strong global optimization ability, which is more suitable for predicting events with fewer related data samples and smaller scales, such as in fruit tree yield prediction events that consider natural factors.

4.4. Making Predictions

Predict the fruit tree yield for the next three years (due to the characteristics of the model, each prediction is different, and the results of a certain prediction are shown in Table **5**).

Table 5: Prediction of fruit tree yield from 2023 to 2025.

Year	Predicted Value (10000 Tons)
2023	978.6
2024	861.4
2025	947.6

These predicted values are closely related to 8 data indicators, and social factors are relatively stable. However, it cannot be ruled out that changes in government strategy may affect the transformation of social factors; The predicted values in this article are obtained from the training results of the original data, and due to the characteristics of the model, each predicted value is different. Therefore, this predicted value is for reference only and has no authority.

5. Conclusion and Suggestions

According to the research results, social factors have the highest correlation with fruit tree yield, but natural factors cannot be ignored. Given the natural situation in Fujian Province, it should also be considered as an important influencing indicator when predicting fruit tree yield. The combination model of the fruit fly algorithm optimized grey neural network used in this article has shown good performance in predicting fruit tree yield, and can also be effectively trained for relatively random natural factors. With the advent of the digital age, the government's demand for refined management of the fruit tree industry is becoming increasingly strong. In view of this, the following suggestions can be made for the government's layout of the fruit tree industry:

1) Expand industrial scale according to local conditions. The disasters in Fujian Province are mainly concentrated in the hilly and mountainous areas of the central and western regions. The government can conduct on-site research to determine development areas and concentrate development, develop deep processing industries, and form industrial clusters; At the same time, a reasonable allocation of special finance will be made to introduce advanced technology, improve fruit tree infrastructure, promote mechanization, intelligence, and green development, improve fruit tree yield and quality, and provide technical training and guidance to help fruit farmers make rational use of resources, scientifically manage fruit trees, improve fruit tree stress resistance and yield stability, and cope with different climate and environmental changes.

2) Make a good prediction plan. Promote meteorological and geological research departments to use annual forecasts of natural factors for the prevention and control of natural disasters and fruit tree yields, coordinate and plan response methods, maintain market supply and demand balance, establish a fruit tree yield prediction system, and formulate reasonable fruit tree resource allocation plans, including arrangements for land use, water resource allocation, fertilization, and pest and disease prevention; At the same time, when predicting a decrease in fruit tree yield, develop an emergency plan for the current year and use the "three in one" approach to safeguard the interests of fruit farmers.

3) Strengthen the ecological environment protection of orchards. Strengthen the ecological environment protection of orchards. Clarify the ecological red line of fruit trees, strengthen the protection of the ecological environment of orchards, establish a monitoring and evaluation system for the ecological environment of fruit trees, regularly monitor and evaluate the ecological environment of orchards, timely discover and solve ecological environment problems, protect the stability and healthy development of the orchard ecosystem, and ensure the sustainability and long-term development of fruit tree production.

Conflict of Interest

The authors have no conflict of interest to declare.

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References

[1] Jiang Z, Jianbo Z. The development of modern chinese fruit industry from the perspective of "alternative agriculture". Agric History China. 2023; 42(04): 56-71.

[2] Lili J, Lisa P, Jinhua Y. Mathematical modeling and data processing. Beijing: Science Press; 2020.

[3] Haijun H. Research on Key Technologies for Precise Application of Water and Fertilizer in Apple Orchards. Zigong: Sichuan University of Light Industry and Technology; 2021.

[4] Shulin H, Huimin L, Liqiang J, Yong L. Research on water demand prediction of fruit trees based on neural network algorithms. J Irrig Drain Eng. 2022; 41(1): 19-24. https://doi.org/10.13522/j.cnki.ggps.2021332

[5] Yanan X. Research on development strategies of Australian nut industry in Chongzuo City, Guangxi. Nanning: Guangxi University; 2022.

[6] Batista APB, Scolforo HF, de Mello JM, Guedes MC, Terra MCN, Scalon JD, *et al*. Spatial association of fruit yield of Bertholletia excelsa Bonpl. trees in eastern Amazon. Forest Ecol Manag. 2019; 441: 99-105. https://doi.org/10.1016/j.foreco.2019.03.043

[7] Chongjiao Z, Xiaolin S, Shuanghong H. Research on refrigerator order demand prediction based on fruit fly algorithm optimized grey neural network. Math Pract Theor. 2017; 47(20): 15-9.

[8] Feng L, Jiangbo X. The way of emergency news propaganda and management for major natural disasters: taking the news and public opinion guidance of Fujian province's defense against super typhoon "Du Suri" as an example. Chinese Journalist. 2023; (09): 83-5.

[9] Feng X, Haihua S, Jiayi W, Ran Z, Junhui W, Huan Y, *et al*. Research on status evaluation of relay protection devices based on grey relational degree. Electr Meas Instrum. 2024; (in press). Available from: https://kns.cnki.net/kcms/detail/23.1202.TH.20240511.0905.004.html

[10] Wang S, Xing Q, Wang X, Wu Q. Demand forecasting model of coal logistics based on Drosophila grey neural network. Int J Syst Assur Eng Manag. 2023; 14(2): 807-15. DOI：https://doi.org/10.1007/s13198-021-01586-x

[11] Wu H, Wang L, Xie M, Wang K, Fu Y. Peak prediction of carbon emissions from electricity based on grey BP neural network. Electron Des Eng. 2024; 32(09): 105-9. https://doi.org/10.14022/j.issn1674-6236.2024.09.022

[12] van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using machine learning: A systematic literature review. Comput Electron Agric. 2020; 177: 105709. https://doi.org/10.1016/j.compag.2020.105709

[13] Dias KOG, Piepho HP, Guimaraes LJM, Guimaraes PEO, Parentoni SN, Pinto MO, *et al*. Novel strategies for genomic prediction of untested single-cross maize hybrids using unbalanced historical data. Theor Appl Genet. 2020; 133: 443-55. https://doi.org/10.1007/s00122-019-03475-1

[14] Dahane A, Benameur R, Kechar B, Benyamina A. An IoT based smart farming system using machine learning. 2020 International Symposium on Networks, Computers and Communications (ISNCC), Montreal, QC, Canada, 2020, pp. 1-6. https://doi.org/10.1109/ISNCC49221.2020.9297341

[15] Sawant D, Jaiswal A, Singh J, Shah P. AgriBot - An intelligent interactive interface to assist f armers in agricultural activities. 2019 IEEE Bombay Section Signature Conference (IBSSC), Mumbai, India, 2019 pp. 1-6. https://doi.org/10.1109/IBSSC47189.2019.8973066

[16] Kumar YJN, Spandana V, Vaishnavi VS, Neha K, Devi VGRR. Supervised machine learning approach for crop yield prediction in agriculture sector. 2020 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2020, pp. 736-41. https://doi.org/10.1109/ICCES48766.2020.9137868

[17] Usha Rani N, Gowthami G. Smart crop suggester In Jyothi S, Mamatha D, Satapathy S, Raju K, Favorskaya M, Eds. Advances in Computational and Bio-Engineering. CBE 2019. Learning and Analytics in Intelligent Systems, vol 15. Springer, Cham; https://doi.org/10.1007/978-3-030-46939-9_34

[18] Pudumalar S, Ramanujam E, *et al*. Crop recommendation system for precision agriculture. Eighth International Conference on Advanced Computing (ICoAC). 2017; pp. 32-36. https://doi.org/10.1109/ICoAC.2017.7951740

[19] Ahamed ATMS, *et al*. Applying data mining techniques topredict annual yield of major crops and recommend planting different crops in different districts in Bangladesh. IEEE/ACIS 16th International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD). 2015; pp. 1-6, https://doi.org/10.1109/SNPD.2015.7176185

[20] Kumar R, Singh MP, Kumar P, Singh JP. Crop Selection Method to maximize crop yield rate using machine learning technique. 2015 International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), Avadi, India, 2015, pp. 138-45. https://doi.org/10.1109/ICSTM.2015.7225403

[21] Reddy PC, Babu AS. Survey on weather prediction using big data analystics. 2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2017, pp. 1-6. https://doi.org/10.1109/ICECCT.2017.8117883

[22] Kishor RV, Shatrughan KP, Balasaheb KK, Sadashiv MB, Sachin V, Gaike VV, *et al*. Agromet expert system for cotton and soyabean crops in regional area. 2018 International Conference on Advances in Communication and Computing Technology (ICACCT), Sangamner, India, 2018, pp. 149-54. https://doi.org/10.1109/ICACCT.2018.8529664

[23] Ghazaryan G, Skakun S, König S, Rezaei EE, Siebert S, Dubovyk O. Crop yield estimation using multi-source satellite image series and deep learning. IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, 2020, pp. 5163-6. https://doi.org/10.1109/IGARSS39084.2020.9324027

[24] Meeradevi, Salpekar H. Design and implementation of mobile application for crop yield prediction using machine learning. 2019 Global Conference for Advancement in Technology (GCAT), Bangalore, India, 2019, pp. 1-6. https://doi.org/10.1109/GCAT47503.2019.8978315

[25] Le TL, Wang JW, Wang CC, Nguyen TN. Automatic defect inspection for coated eyeglass based on symmetrized energy analysis of color channels. Symmetry, 2019; 11(12): 1518. https://doi.org/10.3390/sym11121518

[26] Nguyen TN, Liu BH, Wang SY. On new approaches of maximum weighted target coverage and sensor connectivity: Hardness and approximation. IEEE Trans Network Sci Eng. 2019; 7(3): 1736-51. https://doi.org/10.1109/TNSE.2019.2952369

[27] Rajendrakumar S, Parvati VK, Rajashekarappa, Parameshachari BD. Automation of irrigation system through embedded computing technology. Proceedings of the 3rd International Conference on Cryptography, Security and Privacy. 2019; 289-93. https://doi.org/10.1145/3309074.3309108

[28] Parameshachari BD, Kiran, Rashmi P, Supriya MC, Rajashekarappa, Panduranga HT, *et al*. Controlled partial image encryption based on LSIC and chaotic map. ICCSP 2019: 2019 the 3rd International Conference on Cryptography, Security and Privacy Kuala Lumpur Malaysia: January 19 - 21, 2019, pp. 60-3. https://doi.org/10.1145/3309074.3309107

[29] Ahamed ATMS, Mahmood NT, Hossain N, MT Kabir, Das K, Rahman F, *et al*. Applying data mining techniques to predict annual yield of major crops and recommend planting different crops in different districts in Bangladesh. 2015 IEEE/ACIS 16th International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD), Takamatsu, Japan: 2015, pp. 1-6. https://doi.org/10.1109/SNPD.2015.7176185

[30] Ahmad I, Saeed U, Fahad M, Ullah A, Habib ur Rahman M, Ahmad A, *et al*. Yield forecasting of spring maize using remote sensing and crop modeling in Faisalabad-Punjab Pakistan. J Indian Soc Remote Sens. 2018; 46(10): 1701-11. https://doi.org/10.1007/s12524-018-0825-8

[31] Ali I, Cawkwell F, Dwyer E, Green S. Modeling managed grassland biomass estimation by using multitemporal remote sensing data—a machine learning approach. IEEE J Sel Top Appl Earth Obs Remote Sens. 2017; 10(7): 3254-64. https://doi.org/10.1109/JSTARS.2016.2561618

[32] Ananthara MG; Arunkumar T, Hemavathy R. CRY-An improved crop yield prediction model using bee hive clustering approach for agricultural data sets. 2013 International Conference on Pattern Recognition, Informatics and Mobile Engineering, Salem, India: 2013, pp. 473-8. https://doi.org/10.1109/ICPRIME.2013.6496717

[33] Baral, Kumar Tripathy, Bijayasingh. Yield prediction using artificial neural networks. In: Das VV, Stephen J, Chaba Y, Eds. Computer Networks and Information Technologies. CNC 2011. Communications in Computer and Information Science, vol 142, Berlin, Heidelberg: Springer; 2011, https://doi.org/10.1007/978-3-642-19542-6_57

[34] Bargoti S, Underwood JP. Image segmentation for fruit detection and yield estimation in apple orchards. J Field Rob. 2017; 34(6): 1039-60. https://doi.org/10.1002/rob.21699

[35] Beulah R. A survey on different data mining techniques for crop yield prediction. Int J Comput Sci Eng. 2019; 7(1): 738-44. https://doi.org/10.26438/ijcse/v7i1.738744

[36] Bose P, Kasabov NK, Bruzzone L, Hartono RN. Spiking neural networks for crop yield estimation based on spatiotemporal analysis of image time series. IEEE Trans Geosci Remote Sens. 2016; 54(11): 6563-73. https://doi.org/10.1109/TGRS.2016.2586602

[37] Çakır Y, Kırcı M, Güneş EO. Yield prediction of wheat in south-east region of Turkey by using artificial neural networks. 2014 The Third International Conference on Agro-Geoinformatics, Beijing, China, 2014, pp. 1-4. https://doi.org/10.1109/Agro-Geoinformatics.2014.6910609

[38] Charoen-Ung P, Mittrapiyanuruk P. Sugarcane yield grade prediction using random forest with forward feature selection and hyper-parameter tuning, In: Unger H, Sodsee S, Meesad P, Eds. Recent Advances in Information and Communication Technology 2018. IC2IT 2018. Advances in Intelligent Systems and Computing, vol 769. Springer, 2019. https://doi.org/10.1007/978-3-319-93692-5_4

[39] Everingham Y, Sexton J, Skocaj D. Inman-Bamber G. Accurate prediction of sugarcane yield using a random forest algorithm. Agron Sustain Dev. 2016; 36: Article number: 27. https://doi.org/10.1007/s13593-016-0364-z

[40] Everingham YL, Smyth CW, Inman-Bamber NG. Ensemble data mining approaches to forecast regional sugarcane crop production. Agric For Meteorol. 2009; 149:(3-4), 689-96. https://doi.org/10.1016/J.AGRFORMET.2008.10.018

[41] Fernandes JL, Ebecken NFF, Mora Esquerdo JCD. Sugarcane yield prediction in Brazil using NDVI time series and neural networks ensemble. Int J Remote Sens. 2017; 38(16): 4631-44. https://doi.org/10.1080/01431161.2017.1325531

[42] Filippi P, Jones EJ, Wimalathunge NS, Somarathna PDSN, Pozza LE, Ugbaje SU, *et al*. An approach to forecast grain crop yield using multilayered, multi-farm data sets and machine learning. Precis Agric. 2019; 20: 1015-29. https://doi.org/10.1007/s11119-018-09628-4

[43] Gandhi N, Armstrong L. Applying data mining techniques to predict yield of rice in humid subtropical climatic zone of India. 2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India: 2016, pp. 1901-6.

[44] Goldstein A, Fink L, Meitin A, Bohadana S, Lutenberg O, Ravid G. Applying machine learning on sensor data for irrigation recommendations: revealing the agronomist's tacit knowledge. Precis Agric. 2018; 19(3): 421-44. https://doi.org/10.1007/s11119-017-9527-4

[45] Gonzalez-Sanchez A, Frausto-Solis J, Ojeda-Bustamante W. Predictive ability of machine learning methods for massive crop yield prediction. Spanish J Agric Res. 2014; 12(2): 313-28. https://doi.org/10.5424/sjar/2014122-4439

[46] Jeong JH, Resop JP, Mueller ND, Fleisher DH, Yun K, Butler EE, *et al*. Random forests for global and regional crop yield predictions. PLoS One. 2016; 11(6): 1-15. https://doi.org/10.1371/journal.pone.0156571

[47] Khanal S, Fulton J, Klopfenstein A, Douridas N, Shearer S. Integration of high resolution remotely sensed data and machine learning techniques for spatial prediction of soil properties and corn yield. Comput. Electron. Agric. 2018; 153: 213-25. https://doi.org/10.1016/J.COMPAG.2018.07.016

[48] Matsumura K, Gaitan CF, Sugimoto K, Cannon AJ, Hsieh WW. Maize yield forecasting by linear regression and artificial neural networks in Jilin, China. J Agric Sci. 2015; 153(3): 399-410. https://doi.org/10.1017/S0021859614000392

[49] Tao J, Ning L, Shuting S. Research on water demand prediction in Jixi City based on grey prediction model GM (1,1). Heilongjiang Water Resour Sci Technol. 2024; 52 (04): 26-9. https://doi.org/10.14122/j.cnki.hskj.2024.04.012

[50] Hongmei Z, Chengtao Z. Comparative study on medium and long-term prediction of reservoir inflow runoff based on LSTM and BP neural network. Hydrology. (*in press*). https://doi.org/10.19797/j.cnki.1000-0852.20230413