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Soil Moisture Content Prediction Model for Tea Plantations Based on a Wireless Sensor Network

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Abstract. Suitable soil moisture content (SMC) can not only increase the ability of tea tree roots to absorb and utilize nutrients but also improve the utilization rate of soil nutrients, which can ensure a continuous and stable yield and tea leaf quality. Traditional methods for predicting soil water content generally have low accuracy and efficiency problems. A real-time soil information collection system based on a wireless sensor network was built, and a new predicting SMC Model (AO-SVM) for tea plantations using support vector machine optimized (SVM) by Aquila Optimizer (AO) was constructed and evaluated. The SMC prediction model was established using weather data, soil temperature (ST), soil electrical conductivity (SEC), and PH value (pH), and soil water potential (SWP), and so on. First, the correlation between individual SMC, ST, SEC, pH, SWP was analyzed and parameters with high correlation with soil water content were subsequently identified. The AO-SVM model was utilized to predict the soil moisture content. The experiments showed that the R^2 of AO-SVM model proposed in this paper is 0.925. It indicates that the AO-SVM model is effective and feasible and achieves advantageous performance over long short term memory (LSTM), generalized regression neural network (GRNN), the opposition-based chaotic salp swarm algorithm optimized SVM (OCSSA-SVM), sparrow search algorithm optimized SVM (SSA-SVM), particle swarm optimization SVM (PSO-SVM), and the whale algorithm optimized SVM (WOA-SVM) model, which can help guide the irrigation and fertilization management of tea plantations.

Keywords: hybrid antennas, internet of things, prediction model, soil moisture content

1 Introduction

Tea is a leafy crop with high water demand. Low SMC will seriously affect the yield, quality, biochemical composition, and even next year's tea yield. Factors such as rainfall two months before harvesting, average temperature value in the previous month, and the soil moisture content during the growing season have a significant effect on tea yield. With more rainfall and higher humidity, tea yield and quality are better. If the planting conditions are improper, the tea leaves are prone to aging, low yield and poor quality. Suitable soil moisture not only improves the ability of the root system to absorb and utilize nutrients, but also improves the utilization of soil nutrients.

Proper soil water content and soil electrical conductivity play an important role in agricultural cultivation [1-2]. Water-saving irrigation and application techniques are adopted in tea plantations to solve the problem of drought and water shortage, but there is a key problem that irrigation and application are mainly based on experience, lacking scientific irrigation and application schemes, and there is a great blindness [3-4].

In recent years, Internet of Things (IOT) technology, ZigBee technology, and android technology have been widely used in agriculture, combining sensors to collect parameters such as temperature, humidity, conductivity, and pH and send them to servers through wireless sensor networks, which can monitor the growth environment of crops in real time [5-9], while programmable controllers (PLC), human-machine interface (HMI) technology, fuzzy control, gray predictive control, and many other control methods as well as artificial intelligence and expert systems have been applied in irrigation in agriculture [10-15].

Soil water content monitoring methods have been the focus of scholarly research.Soil moisture content is measured by both direct and indirect methods. The main methods are the gravimetric method, neutron probe, dielectric method, tensiometer, resistance block, thermal heat probe, and soil psychrometer [16-18]. Soil moisture content mathematical models can then be constructed using statistical methods, random forests, neural networks, support vector machines, or a combination of these methods to determine the need for water monitoring [19-25].

Using data mining and machine learning techniques, an indirect measurement of soil water content was constructed to calculate soil water content using parameters such as soil temperature, atmospheric temperature, hu-

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midity and leaf color as predictors [26-27].

Prediction of soil water content using parameters such as temperature and humidity was studied utilizing gray neural networks with excellent results [28]. The soil water content prediction model constructed using ELM to build a nonlinear model with less influence of training factors was unable to use technologies such as IoT [29]. The combination of a BP neural network and LSTM deep learning can give a soil moisture prediction model for tea plantations but lacks a model interpretability index to performance description [30]. There are also prediction models for citrus soil moisture content and conductivity given with high accuracy using IoT and LSTM models, which can be utilized to guide irrigation management [31].

The application of monitoring systems makes it possible to provide an effective method for environmental monitoring in agriculture. In the process of wireless transmission, the transmission speed, transmission distance and transmission quality are limited by the installation location and affected by obstacles. In the complex environment of environmental monitoring of crops, the existing monitoring system, which has highlighted the disadvantages, is clearly unable to meet the needs of practical applications. Tea trees are mostly planted in mountainous and sloping areas, and there are trees, mountains and other obstacles in the tea plantations, which limit the distance of wireless communication and affect the quality of communication. So it is difficult to carry out large-scalemoitoring. Also，the prediction methods mentioned above are subject to some problems: the applications are limited, the models are influenced by experience, BP neural networks are slow to converge, LSTM networks require high data and network structure, and SVM models are susceptible to parameter taking.

Based on the above questions, the objectives of this paper are to (1) propose a solution for wireless communication of crops in complex environments; (2) investigate the correlation between soil temperature (ST), soil electrical conductivity (SEC), and PH value (pH), and soil water potential (SWP); (3) determine the feature inputs for the prediction model; (4) construct and evaluate a new predicting SMC Model (AO-SVM) for tea plantations using support vector machine optimized (SVM) by Aquila Optimizer (AO) .

2 Materials and Methods

2.1 System Structure

Because planting tea plantations in Liuzhou is concentrated in mountainous and sloping areas, tea trees are planted in high density and often affected by obstacles, which limit the communication distance of wireless sensor nodes and make it difficult to carry out large-scale information collection and control. To ensure the collection of tea plantation soil information, a regional monitoring method is used. Therefore, the hardware design of tea plantation soil information collection systems includes the design of sensor collection nodes and gateways, where the sensor collection nodes are responsible for collecting and transmitting sensor data to the gateway. The gateway is responsible for sending commands to the nodes and uploading the collected data to the cloud server. The communication between the gateway and the remote server is through wireless communication and the transmitted data are finally stored in the database for further analysis. The overall structure diagram is shown in Fig. 1.

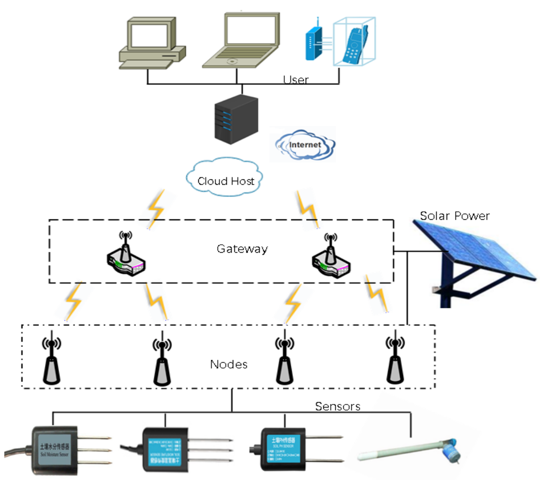

Fig. 1. System framework

To improve communication quality and distance, the system adopts a hybrid antenna communication mode. The antenna can be divided into two types: an omnidirectional antenna and a directional antenna. The omnidirectional antenna is a nondirectional, 360° uniformly radiated antennae covering a large area. In contrast, directional antennas are one or more antennas with a particularly strong ability to communicate and receive electromagnetic waves in a particular direction, while in another direction the transmission ability is zero or very small. Directional antennas are also given the advantages of communication distance, high gain, fast transmission speed, and strong anti-interference ability. Omnidirectional antennas use point-to-many communication, while directional antennas are appropriate for point-to-point communication over a longer distance. The sensor nodes in the tea garden real-time soil information collection system are responsible for sensing the data changes, and then sending the data to the gateway node through the wireless communication module; the communication distance and direction requirements are not high, so they are equipped with an omnidirectional antenna. The gateway node collects the data and then sends it to the server; the communication requires high reliability, so it is equipped with a directional antenna under the control of a stepper motor, which can realize horizontal direction 360° rotation to ensure that the data from the sensor nodes can be received [31-34].

To ensure the system operation stability, optimized solutions are also adopted in the network design, node software design, and gateway collaboration design.

Network design. Sensor nodes and gateway nodes are installed in different tea plantation monitoring areas, and the data transmission performance and service life of the nodes needs to be considered. Since tea plantations are mostly located in mountainous and sloping areas with high tea tree planting density and are often affected by obstacles, the nodes are deployed with a diamond structure to guarantee the data transmission communication distance.

Node software design. Sensor nodes are an important component of the tea garden soil information monitoring system, and after collecting data from the sensors, they are transmitted to the gateway through the wireless sensor network. The entire process undertakes a large number of data transmission tasks. Low power consumption is the main consideration for the sensor node software design. The sensor node has to be set into two modes, normal mode and hibernation mode [35-36]. When data acquisition is required, the sensor node is in normal working mode and should enter into hibernation mode after the acquisition is completed, retaining only the clock wake-up mechanism, or using a timed-on mode and collecting data to save energy.

Gateway collaboration design. The gateway is in charge for parsing the server's instructions sent to the sensor nodes and transmitting data to the server. Most traditional monitoring systems use a single gateway model. In large-scale tea garden monitoring, due to the large quantity of data transmitted, there are certain shortcomings in the communication efficiency and stability; to ensure the system stability and data transmission quality, the multi gateway collaboration mechanism is used. The multiple gateways collect node data in a load-balanced manner; when there is a network abnormality, the data are first saved in the memory card, and when the network is restored, the collected data are uploaded to the server to achieve maximum data loss avoidance, thus improving system stability and reliability [37].

2.2 Data Acquisition Processing

The node data are transmitted to the gateway, which is incharge for sending data to the remote server to complete the data transmission. The system in this paper was built and the official data collection period was from October 5, 2020, to November 16, 2020. The aggregated data package was utilized to count the parameters such as soil water content, soil conductivity, and soil temperature on that day and calculate the data for every 1-hour, 6-hour, 12-hour, and 24-hour interval. Because each environmental parameter has a different order of magnitude, each parameter has to be normalized in the data preprocessing stage. The data were reprocessed using the [0, 1] standardization, and the abnormal values were eliminated by 3σ criteria. After averaging the reprocessed data for each node, correlation analysis was performed for each environmental parameter with soil moisture and conductivity [33].

2.3 Support Vector Machine (SVM) [38]

Suppose the input sample, which is defined by equation (1).

$$Q = \{(\mathrm{x}_1, y_1), (\mathrm{x}_1, y_1), \cdots, (\mathrm{x}_1, y_1)\} \qquad y_i \in R. \tag{1}$$

Regression analysis was performed according to Equation (2).

$$\mathrm{f}(x) = \mathrm{w}^T x + b. \tag{2}$$

Where w and b are the weight and bias values respectively of SVM model.

According to the SRM criterion, a convex quadratic programming problem is obtained by converting equation (2).

$$\min_{\mathrm{w\,b}} \frac{1}{2}\|w\|^2 + \mathrm{K}\sum_{\mathrm{i}=1}^{\mathrm{m}}\left(\xi_{\mathrm{i}} + \hat{\xi}_i\right). \tag{3}$$

$$\mathrm{s.}t.\begin{cases} f(x_i) - y_i \le \varepsilon + \xi_i \\ y_i - f(x_i) \le \varepsilon + \hat{\xi}_i \\ \xi_i \ge 0, \hat{\xi}_i \ge 0, \quad i = 1,2,\cdots,m \end{cases}. \tag{4}$$

where K represents the penalty factor, ξ_i and $\hat{\xi}$ are the introduced relaxation

a_i and $\hat{a}_i$ are Lagrangian multipliers are introduced to solve Equation (3), and then the regression function of the obtained SVM regression model is defined as Equation (5),

$$\mathrm{f}(x) = \sum_{i=1}^{m}(a_i - \hat{a}_i)C(x_i, x_j) + \mathrm{b} \tag{5}$$

where $\mathrm{b} = y_i + \varepsilon - \sum_{i=1}^{m}(a_i - \hat{a}_i)C(x_i, x_j)$.

SVR model performance is affected by the kernel function and penalty factor, which are needed to be optimized.

2.4 Aquila Optimizer (AO)

The Aquila Optimizer (AO) proposed by Laith Abualigah, is a new population-based optimization method. The optimization process of AO is represented by four methods, which are selection step, exploring step, exploiting step, and swooping step [39].

In expanded exploration step (X_1), the Aquila selected the search space by high soar with the vertical stoop, and the position is updated by Equation (6).

$$\mathrm{X}_1(t+1) = X_b(t) \times \left(1 - {}^{\mathrm{t}}\!/\!_{T}\right) + \left(X_M(t) - X_b(t) \times rand\right). \tag{6}$$

Where $\mathrm{X}_1(t+1)$ indicates the position of the next iteration, which determined by X_1, $X_b(t)$ is the best-obtained solution position, $X_M(t)$ indicates the locations mean value of the current solutions, and t and T indicate the current iteration and the maximum number of iteration, respectively;

In narrowed exploration step (X_2), Aquila explored bifurcated search space using contour flight and short-range gliding attacks and its position is updated by Equation (7).

$$\mathrm{X}_2(t+1) = X_b(t) \times \mathrm{levy}(D) + X_r(t) + (y-x) \times rand. \tag{7}$$

Where $\mathrm{X}_2(t+1)$ indicates the position of the next iteration, which determined by X_2, D indicates dimension space, levy（D）is the levy flight distribution function, $X_r(t)$ is a random number of [1, N].

In expanded exploitation step (X_3), Aquila explores the convergent search space by low flight with a slow descent attack and its position is updated by Equation (8).

$$\mathrm{X}_3(t+1) = (X_b(t) \text{-} \mathrm{X_M}(\mathrm{t})) \times \alpha - rand + ((UB - LB) \times rand + LB) \times \delta. \tag{8}$$

Where $\mathrm{X}_3(t+1)$ indicates the position of the next iteration, which determined by X_3, UB and LB represent the upper limit and lower limit of the area, α and δ are an adjustment parameter that takes the value of 0.1.

In narrowed exploration (X_4), Aquila swooped by walk and grab prey and its position is updated by Equation (9).

$$\mathrm{X}_4(t+1) = X_b(t) \times \mathrm{QF} \text{-} (\mathrm{G}_1 \times X(t) \times rand) - G_2 \times levy(D) + rand \times \mathrm{G}_1. \tag{9}$$

Where $\mathrm{X}_4(t+1)$ indicates the position of the next iteration, which determined by X_4, QF refers to a function of the balanced search strategy, which is defined as Equation (10), G1 denotes the various motions of the tracked prey, which is calculated by Equation (11), and G2 is the flight slope of the tracked prey, which is a decreasing value from 2 to 0 and is calculated using Equation (12).

$$\mathrm{QF}(\mathrm{t}) = t^{\frac{2 \times rand - 1}{(1-T)^2}}. \tag{10}$$

$$G_1 = 2 \times rand - 1. \tag{11}$$

$$G_2 = 2 \times \left(1 - \frac{t}{T}\right). \tag{12}$$

2.5 SVM Model Optimized by AOA

The steps of the algorithm are as follows:

(1) Initialize the relevant parameters in AO and SVM;

(2) The fitness value of AO is calculated with MSE of the predicted value of SVM, which is defined as Equation (13) [40].

$$fitness = \arg\min(MSE_p) = \frac{1}{\mathrm{M}} \sum_{n=1}^{M} (y_p - y_r)^2. \tag{13}$$

Where y_p represents the predicted value, y_{r} represents the measured value.

(3) Calculate the AO value to select strategy and update the position;

(4) Find optimal position value

(5) Apply optimized values for SVM network prediction.

3 Experimental Results and Analysis

3.1 Data Correlation Analysis

Exploratory data analysis (EDA) is a method proposed by the American statistician John Tukey in the 1960s to explore existing data information with as few a priori assumptions as possible and to explore relationships and patterns among data by graphic, tabulation, equation fitting, and calculation of characteristic quantities [41]. Correlations between individual soil moisture content, soil conductivity, soil temperature, soil moisture, and soil water potential were analyzed using heat maps, as showed in Fig. 2.

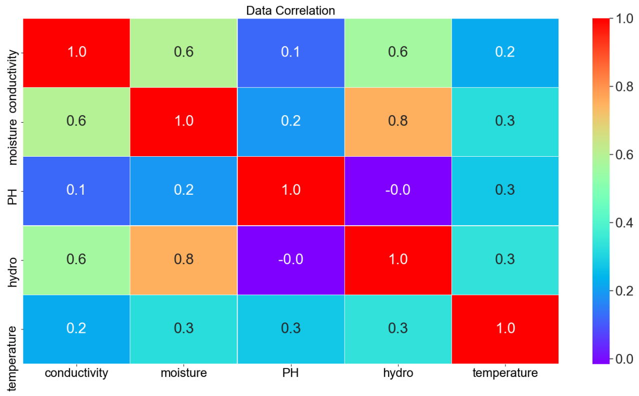

Fig. 2. Parameter correlation

In Fig. 2, conductivity represents soil electrical conductivity, moisture represents soil moisture content, pH represents pH value, hydro represents soil water potential, and temperature represents soil temperature.

Fig. 2 shows a moderate to high correlation between the soil moisture content and the soil water potential and the soil moisture content, both were approximately 0.6, and the correlation of soil moisture content with the soil temperature and pH was only 0.3 and 0.2, which indicates that soil conductivity is less influenced by soil temperature and pH value. A higher value indicates myasthenia higher correlation between them. It can be drawn that the higher correlations with soil moisture content are, in order, soil water potential, soil conductivity, soil temperature, and soil moisture.

3.3 Model Evaluation Criteria

The performance evaluation metrics of the network were measured using the decision system (R^2) [42], which is defined in Equation (14).

$$R^2 = \frac{\sum_{n=1}^{M}\left(y_{pred} - \overline{y_{real}}\right)^2}{\sum_{n=1}^{M}\left(y_{\mathrm{real}} - \overline{y_{real}}\right)^2}. \tag{14}$$

where y_{pred} represents the predicted value, y_{real} represents the measured value, $\overline{y_{real}}$ represents the mean of the measured value, and M represents the sample value.

3.4 Model Performance Analysis

Parameters collected by this system are mainly SMC, SWP, ST, pH, and SEC. Data correlation experiments show that soil water content is under a high correlation with soil water potential and soil conductivity, both above 0.5. Therefore, SWP and SEC can be used as input to the prediction model. Although the correlation between SMC and ST and pH of soil conductivity was 0.4 and 0.3, respectively, this could also be used as input to the prediction model to improve model prediction accuracy.

The data were reprocessed using the [0, 1] standardization, and the abnormal values were eliminated by 3σcriterion. Five-hundred sample data were randomly selected as the training set, and the remaining 135 sample data were used as the test configure in train and test the soil conductivity prediction model.

The processed data were randomly disrupted, and then the first 500 groups were taken as the training set, and the other 136 groups were used as the test set. In order to be able to effectively test the performance of the AO-SVM model, several experiments are required and the average value is taken as the final result. Prediction results of the AOA-SVM model are shown in Table 1.

Table 1. Test results of AO-SVM prediction model

Item	1	2	3	4	5	Average
R^2	0.9366	0.9057	0.9173	0.9128	0.8947	0.9134

As shown in Table 1, the mean value R^2 of AO-SVM model is 0.9134; and it can be seen from Fig. 3. that the predicted values of the AO-SVM model can capture the true values well, which indicates that this model has good prediction performance and strong generalization ability and can be applied to the prediction of soil water content.

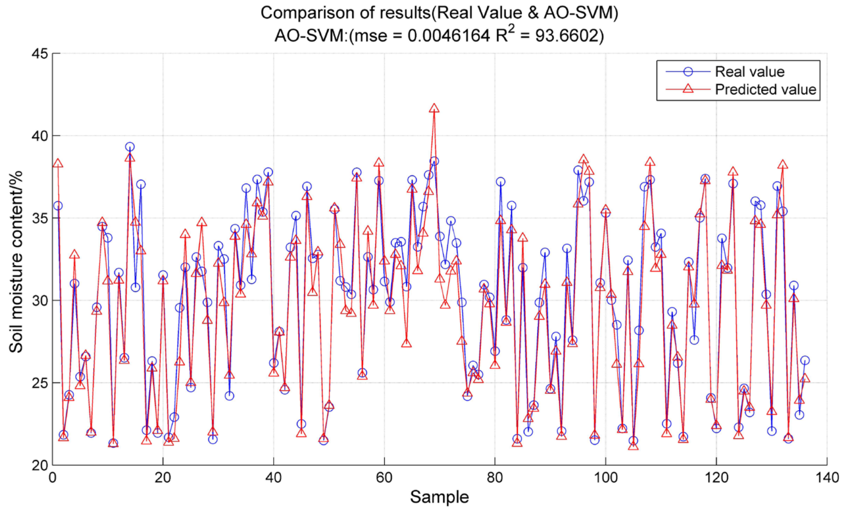

Fig. 3. Prediction result of AO-SVM model

3.5 Comparison with Existing Algorithms

The performance of AO-SVM was compared the performance of AO-SVM with existing algorithms such as LSTM, GRNN, OCSSA-SVM, SSA-SVM, PSO-SVM, and WOA-SVM to verify the superiority of the AO-SVM algorithm. Results in the Table 2 are the average of the results of ten replicated experiments.

Table 2. Model performance

Model	R^2
AO-SVM	0.925
LSTM	0.811
GRNN	0.126
OCSSA-SVM	0.901
SSA-SVM	0.864
PSO-SVM	0.845
WOA-SVM	0.859

It can be seen that the GRNN model had the worst prediction performance among the eight models, with an R^2 of 0.126; the LSTM model, SSA-SVM model, PSO-SVM model, and WOA-SVM model had slightly better prediction performances, with an R^2 of 0.811 for the LSTM model, R^2 of 0.864 for the SSA-SVM model, R^2 of 0.845 for the PSO-SVM model, and an R^2 of 0.859 for the WOA-SVM model. The R^2 values of both the OCSSA-SVM and AO-SVM models were above 0.9. In addition, the AO-SVM model proposed in this paper had the best prediction performance among the eight models, with an R^2 of 0.925. The experiments showed that the method is effective and feasible and achieved an advantageous performance over the LSTM, GRNN, OCSSA-SVM, SSA-SVM, PSO-SVM, and WOA-SVM models.

4 Conclusion

This paper proposed a soil information collection system using a wireless sensor network, which can collect soil temperature, water content, conductivity, pH value, and water potential data in real-time and transmit the data to a remote server using wireless sensor network technology. The system was then used to build a soil water content prediction model for tea plantations to make predictions using the BP-AdaBoost model. The experiments showed that the tea garden soil water content prediction model achieved good prediction results. Our work is summarized as follows.

(1) A soil information collection system based on a wireless sensor network was built. We designed sensor circuits for soil temperature, soil moisture content, soil electrical conductivity, pH value, and soil water potential. Data acquisition was completed and the data was transmitted to a remote server using wireless sensor network technology. The collect data was used to build a soil moisture content prediction model for tea plantations.

(2) A solution for wireless communication of crops in complex environments was proposed. To improve data transmission distance, transmission rate and transmission quality, hybrid antenna communication mode is adopted. Sensor nodes are equipped with an omnidirectional antenna, which can improve communication distance, and gateway node is equipped with a directional antenna under the control of a stepper motor, which can realize horizontal direction 360° rotation to ensure that the data from the sensor nodes can be received. To ensure the system operation stability, optimized solutions are also adopted in the network design, node software design, and gateway collaboration design.

(3) The correlation of the parameters in the soil water content prediction model was determined. The correlation of each parameter was analyzed by using EDA and heatmaps; it was determined that the higher correlation of soil water content is soil water potential, soil conductivity, soil temperature, and soil moisture in order.

(4) A new predicting SMC Model (AO-SVM) for tea plantations using support vector machine optimized (SVM) by Aquila Optimizer (AO) was constructed and evaluated. Soil moisture content was predicted by using soil water potential, soil electrical conductivity, soil temperature, and pH value together. The AO-SVM model proposed in this paper had the best prediction performance among the eight models, with an R^2 of 0.925. The experiments showed that the method is effective and feasible and achieved an advantageous performance over the LSTM, GRNN, OCSSA-SVM, SSA-SVM, PSO-SVM, and WOA-SVM models.

Some issues in the paper also remain to be further discussed.

(1) Direction of radio communication quality. Since radio signals propagate in an environment with vegetation cover, various propagation mechanisms such as direct, reflection, bypassing, and scattering may exist, and there may also be effects such as obstacles. Therefore, further research on radio communication is needed to improve the quality and reliability of radio communication.

(2) Improvement of soil water content predicting model. Since the soil moisture content is influenced more by other environmental factors, further in-depth research is needed to study the relationship between soil water content and meteorological parameters, and integrate them into the model to obtain better results.

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