Net Photosynthesis Prediction by Deep Learning for Commercial Greenhouse Production

Abstract—The amount of net photosynthesis of leaves is a significant factor for the growth of plants. Therefore, monitoring the real-time net photosynthesis plays an essential role in improving the quality of productions in commercial greenhouses. Net photosynthesis mainly depends on three environmental parameters, that are light level, temperature, and CO2 concentration. However, it is challenging to calculate accurate net photosynthesis due to the highly nonlinear relation. In this paper, Deep Learning (DL) is utilized to model this relationship in order to predict the net photosynthesis based on the three inputs. Firstly, the architecture of a Deep Neural Network (DNN) model is designed according to the features of this problem, and three activation functions are concerned for the DNN model design. Secondly, a training dataset is established, and two schedules of Learning Rate (LR), fixed LR and exponential decay LR, are elaborated. Then, to select the optimal hyperparameters for the DNN model, experiments of hyperparameters tuning related to activation functions and LR schedules are implemented, respectively. Finally, through a comprehensive evaluation of the training speed and the prediction accuracy, a DNN model that is with ReLU activation function and decay LR is determined. This DNN model can perform a dramatically high prediction accuracy in a fast training convergence speed for solving the proposed net photosynthesis prediction problem.

Keywords—Deep Learning (DL), Deep Neural Network (DNN), Exponential decay learning rate, Net photosynthesis (PN), Commercial greenhouse

I. INTRODUCTION

Nowadays, Deep Learning (DL) technologies have been widely applied for solving complex nonlinear problems successfully [1]. Among the areas of these problems, agriculture is a significant direction of DL application [2]. Agricultural problems are inherently complex since they involve dynamic processes, each including multiple nonlinear factors that interact mutually [3]. Therefore, it is challenging for conventional approaches to deal with such highly nonlinear complexity [4, 5]. As a result, many researches have been committed to apply DL for solving complex agricultural problems.

In [6], a Deep Neural Network (DNN) model of the temporal dynamics of plant photosynthesis related to the gross primary product is established for two types of vegetables. Three architectures of DNN models are designed in the study, respectively. These different neural network models involve a feedforward Neural Network and two networks with the historical and current information, long short-term memory and transformer. The study also provides the relation of photosynthesis of plants with the environmental elements, such as temperature, light level, water level, etc. Then, these models are trained by a two-week practical dataset to figure out the most suitable DNN model.

The authors of [7] propose a DNN model is designed for predicting the yield of productions through remote sensing data. The paper introduces a new dimensionality reduction technique to overwhelm the shortage of training images so that a training dataset of soybean production in America can be established. Then, the designed DNN is trained according to the histograms to evaluate the performance of the model. Finally, a Gaussian Process component is introduced into the neural network so that the proposed model can be applied to spatiotemporal dependencies.

A convolutional neural network (CNN) and a long short-term memory (LSTM) are combined in [8] to identify which growth stage the oilseed rape crops are in based on the exact nutrient status. First, CNN is utilized to extract the crops’ features of the individual stage from historical images. Then, these distinctive features are inputted into an LSTM to classify the oilseed rape into nine stages. Through training and testing based on a two-year dataset, this DL combination method performs a higher classification accuracy Comparing with the conventional approaches.

In this study, Deep learning technology is innovatively utilized on photosynthesis prediction based on multiple environmental factors; light level, temperature, and CO2 concentration. As we know, there is no previous research applying DL to solve this problem. The impacts of hyperparameters of the designed DNN model, that are activation function and the learning rate, are explored in this study. Through the analysis and the comparison of the training results, the optimal hyperparameters are determined finally. The DNN model suggested by this paper provides an innovative effective approach to handle the photosynthesis prediction to help growers monitor the photosynthesis of productions according to the real-time environmental data.

The remaining part of this paper is organized as follows. In section II, the net photosynthesis prediction problem in greenhouse systems is introduced. Section III elaborates on the architecture design of the DNN model. Section IV presents the dataset establishing process and the training strategy. Then, section V proposes the experiments of exploring the performance of different activation functions and the impact of fixed and decay learning rate. The experimental results are analyzed and compared in section VI to determine the suitable DNN model for solving the proposed problem. Finally, the conclusion of this paper is stated in section VII.
II. PROBLEM DESCRIPTION

Greenhouse systems play a crucial role in plant production in Nordic countries due to the natural environmental limitations [9], such as insufficient natural light, low average annual temperature, etc. In greenhouses, various actuators are installed to provide a suitable environment for the requirements of different stages of plant growth [10]. For example, the artificial lighting system produces supplemental light, the ventilation system can regulate the CO2 concentration, and the heating system can adjust the indoor temperature [11].

Net photosynthesis is an important parameter to influence the performance of plant production, which is determined by multiple environmental elements. The prediction of net photosynthesis under a specific situation is key to obtain optimal production by adjusting the relevant environmental parameters [12].

Light level, temperature and CO2 concentration are the environmental parameters that are most relevant with the net photosynthesis on the surface of leaves in greenhouse systems. For the net photosynthesis of plants, the efficient element in light is the photosynthetically active radiation (PAR). The net photosynthesis and these three parameters represent a nonlinear relation. These parameters influence and restrict each other on their impact on net photosynthesis. Fig. 1 is a demonstration of the relation between net photosynthesis and the three elements. Mesh (a), (b) and (c) in Fig. 1 are the net photosynthesis over PAR and temperature when the CO2 concentration is 450 ppm, 950 ppm and 1450 ppm, respectively. From the meshes, it indicates that the relations between net photosynthesis and the three elements are a complex nonlinear tendency. Therefore, the prediction of real-time net photosynthesis according to a given group of environmental parameters is a complex problem in practice.

Fig. 1. Net photosynthesis over the light level (PAR), temperature and CO2 concentration

The ranges of the three environmental parameters are listed in TABLE I. The large difference among the ranges of the inputs is another difficulty for the net photosynthesis prediction problem.

III. DESIGN OF DNN MODEL

In this section, a DNN model is designed for solving the proposed problem regarding net photosynthesis prediction according to multiple inputs. The architecture of the DNN model and the according configurations are elaborated.

The architecture of the DNN model for the net photosynthesis prediction problem is shown in Fig. 2. There are three inputs involved in the input layer, including light level PAR, temperature and CO2 concentration. Due to the differences in input ranges, this problem becomes large (TABLE I), and a normalization layer, therefore follows the input layer to normalize the input ranges between [0, 1]. The normalization equation is:

$$x^{(i)}_k = \frac{x^{(i)}_k - \mu_k}{\sigma_k}$$  \hspace{1cm} (1)

Here, $x^{(i)}_k$ indicates the $i^{th}$ sample of $k^{th}$ input in the training dataset, where $i \in [1, m]$ and $k \in [1, 3]$, and $m$ is the number of samples in the training dataset. $x^{(i)}_k$ denotes the normalized $x_k$, $\mu_k$ and $\sigma_k$ are the mean and the standard deviation of $x_k$, respectively. The definition of $\sigma_k$ is in (2).

$$\sigma_k = \sqrt{\frac{\sum_{i=1}^{m}(x^{(i)}_k - \mu_k)^2}{m}}$$  \hspace{1cm} (2)

There are seven hidden layers in this DNN model and the number of units, excepting bias, in each layer is 64. Therefore, the total number of parameters is 25,281, including bias. The mathematical calculation of the output of an individual neuron follows:

$$h_{neuron} = f((X, \theta) + b)$$  \hspace{1cm} (3)

where $X$ and $\theta$ are the input vector of the neuron and the corresponding parameter vector. $b$ denotes the bias unit and the parameter of $b$ is one. $\langle \cdot , \cdot \rangle$ represents dot production of the two vectors, and $f(\cdot)$ is the activation function [13].
To compare the impacts of activation functions on the net photosynthesis prediction accuracy for designing the DNN model, three mainstream activation functions are experimented in this paper, respectively. They are Sigmoid, Rectified Linear Unit (ReLU) and Hyperbolic Tangent (Tanh) [13]. Due to their advantages of solving nonlinear prediction problems as activation functions in DNN, these three activation functions have been widely utilized [14-16].

There is one output of the proposed DNN model, which is the hypotheses of net photosynthesis.

IV. DATASET AND TRAINING

The structure of the training dataset and the process training of the proposed DNN model is elaborated in this section. The purpose is to collect the parameters of the DNN model.

A. Dataset

In [12], an experimental formula is utilized to calculate the net photosynthesis based on light level (PAR), CO2 concentration and temperature, so that the authors can optimize the climate in the greenhouse for maximizing the leaf net photosynthesis while saving energy consumption. In this paper, the training dataset is established based on the experimental formula and the experimental results of [12], such as the relationship among the parameters, the ranges of inputs and outputs etc.

As a result, 84,280 samples are involved in the training dataset of this paper. The inputs of individual samples are light level (PAR), CO2 concentration and temperature, and the output is the respective net photosynthesis.

The sample allocation is that 80% of the training data (67,424 samples) are used for training, and 20% (16,856 samples) is for the validation during the training process to avoid overfitting.

B. Training

To accelerate the training process, Adaptive Moment Estimation (Adam) optimization is utilized to optimize the parameters of the proposed DNN model. As an adaptive optimization algorithm, the gradient descent of Adam also involves local optimization by selecting a local distance measurement based on the historical parameters [17].

Two strategies of the Learning Rate (LR) configurations for the optimizer are conducted in this paper. The traditional strategy is to figure out a fixed value, which is one of the largest LRs that can make the DNN training converge. Thus, this fixed LR is a trade-off between the optimization speed and the convergence.

In order to quickly approach the optimal point during the training, the LR should be set to a large value. However, a large LR has a risk of oscillation beyond the optimal point or even diverging [18]. On the contrary, if the LR is very small, a higher possibility of convergence can be guaranteed, but makes the training process longer. For solving this dilemma, this paper also applies the second LR configuration strategy, an exponential decay schedule. The LR is updated by exponential decay as (4).

\[
LR_{de} = LR_0 \cdot r_{de}^{\frac{epoch}{stp_{de}}} \tag{4}
\]

where \(LR_0\) is the initial LR, \(r_{de}\) is the decay rate and \(stp_{de}\) is the decay step. All of these hyperparameters are setup before training starts. The learning rate \(LR_{de}\) is decayed over the training epoch by an exponential relationship.

For evaluating the prediction performance of the proposed DNN model, the prediction loss is defined as:

\[
L = \frac{\sum_{i=1}^{m} |h^{(i)} - y^{(i)}|}{m} \tag{5}
\]

where \(h^{(i)}\) and \(y^{(i)}\) are the hypotheses of the DNN and actual output value in the training dataset of the \(i^{th}\) sample.

The design and training of the proposed DNN are based on TensorFlow 2.1.0 in Python 3.7 on Windows OS. The GPU for training the DNN is NVIDIA Tesla T4 GPU with 16 GB memory.

V. EXPERIMENTS

In this section, experiments with different activation functions and two tuning strategies of the learning rate are performed to analyze the impacts of various hyperparameter on the prediction problem. The configurations of hyperparameters for the experiments are summarized in TABLE II.

<table>
<thead>
<tr>
<th>TABLE II. HYPERPARAMETER CONFIGURATION</th>
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<tr>
<td><strong>Layer</strong></td>
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<td>Output layer</td>
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<td>Number of training epochs</td>
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A. Activation function

For comparing the influence of the mainstream activation functions- Sigmoid, ReLU and Tanh- on the proposed DNN for the net photosynthesis prediction problem, corresponding experiments are committed, respectively.
The hyperparameters of the experiments on the three activation functions are configured consistently. The values of biases are all initialized to zero. To obtain a trade-off between training speed and reaching convergence, the LR is fixed to 0.0003, which is one of the highest LRs for training convergence. The maximum training epoch is set to be 200.

The demonstrations of the three activation functions and the respective relations of the loss, including training loss and validation loss, along with training epoch in the three experiments are shown in Fig. 3.

The accuracies of the training experiments with different activation functions are 93.52%, 99.24% and 86.43%, respectively, and the comparison result is shown in Fig. 4.

B. Learning rate

Here, a fixed LR and an exponential decay learning rate work on the optimizer Adam, respectively, to compare the influence on the training process in this problem.

Regarding the fixed LR, it is configured to 0.0003, which is consistent with the one in the activation comparison experiments.

Concerning the exponential decay LR, it follows the expression in (4). The initial learning rate $LR_0$ is to 0.001, the decay rate $r_{de}$ is 0.9, the decay step $stp_{de}$ is 1, and the decay process is with no staircase. Therefore, the learning rate $LR_{de}$ is decayed over the training epoch by an exponential relationship. When the maximum training epoch is 200, the decayed LR over epoch number is shown in Fig. 5.

In Fig. 5, the LR is the highest at the initial training process, which can accelerate the training speed when the loss is large. Then the LR is decayed by an exponential tendency along with the epoch increases and reduces to be close to zero after around 50 epochs. A smaller LR reduces the risks of divergence and oscillation when the training loss is decreasing. That is, the parameters are closing to the optimal point.

The hyperparameter configurations in the two experiments, which are with fixed and decay LRs, are consistent, and the same with the experiments on the impact comparison of activation functions. The training loss and the validation loss of the two experiments are shown in Fig. 6.
During the flat process of training, the training loss of the DNN with decay LR is smooth and nearly without obvious oscillation. The accuracy of the DNN with decay LR is 99.32%, which is slightly higher than fixed LR. Thus, the decayed LR reduces the oscillation during the convergence process dramatically, compared with the loss plot of fixed LR.

In conclusion of the two experiments related LR, exponential decay LR can shorten training time effectively without comprising the prediction performance compared with fixed LR.

VII. CONCLUSION

In this paper, Deep Learning is utilized in commercial greenhouse systems to solve the net photosynthesis prediction problem based on multiple environmental parameters. The influence of the hyperparameters – activation functions and learning rate, on the prediction accuracy are explored and the experimental results are analyzed. Through comparing the results, this paper contributes to the suggestions on designing DNN models for high nonlinear problems in comprehensive areas.

First, some representative researches on agricultural areas are introduced, and the contributions of this paper are presented. Next, the architecture of a DNN model is designed and two of the hyperparameters – activation functions and learning rate – are tuned to optimize the DNN model according to the features of the problem. Then, experiments on training the proposed DNN model with different hyperparameters are implemented and the results are discussed. Finally, by comparing with other hyperparameter tuning strategies, a DNN model, which is with ReLU activation function and an exponential decay learning rate, is determined to solve the net photosynthesis modeling problem. This DNN model performs a high prediction accuracy (99.32%) and a fast convergence speed during training.

However, there are still some limitations in this paper that can be improved in future research. For example, only the impacts of two of the hyperparameters are experimented and analyzed in this paper. The other hyperparameters, such as the hidden layer number, the applied optimizer, etc., may be able to dramatically enhance the performance of the DNN model potentially. Besides, the use of other advanced learning rate tuning strategies, such as an exponential decay sine wave learning rate in [19] and an adaptive learning rate tuning strategy in [20], benefits the training acceleration and the modeling accuracy of DNN. Thus, these researches can provide new ideas for handling this issue.

REFERENCES


