Indoor Hydroponic Greenhouses

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Indoor hydroponic greenhouses are becoming increasingly popular for sustainable food production. On the other hand, precise control of the climate conditions inside these greenhouses is crucial for the success of the crops. Time series deep learning models are adequate for climate predictions in indoor hydroponic greenhouses, but a comparative analysis of these models at different time intervals is needed.

time series hydroponic greenhouse climate prediction deep learning

1. Introduction

Indoor hydroponic greenhouses provide an efficient and sustainable method of food production in urban areas where arable land is available. In hydroponic systems, plants are grown in a nutrient-rich solution instead of soil, which allows for precise control of the growing conditions. On the other hand, maintaining optimal growing conditions inside the greenhouse is crucial for achieving high crop yields [1]. The climate conditions inside the greenhouse, including temperature, humidity, and CO_2 concentration, need to be monitored and controlled to ensure optimal plant growth and development. Climate prediction in indoor hydroponic greenhouses is complex due to the interdependence of different variables and their nonlinear relationships. Traditional methods for climate predictions, such as statistical models, have limitations in capturing the complex patterns and relationships between different variables [2][3][4][5]. Time series deep learning models have the potential for analyzing sequential data and making accurate predictions. These models can learn from the historical climate data and identify patterns and trends that are difficult to detect using traditional methods [6].

This study compared the performance of three commonly used time series deep learning models to predict the climate conditions in an indoor hydroponic greenhouse at different time intervals: Deep Neural Network (DNN), Long–Short Term Memory (LSTM), and 1D Convolutional Neural Network (1D-CNN). The dataset used in this study was collected over a week at one-minute intervals and prepared at four different intervals: 1, 5, 10, and 15 min. The performance of the models was evaluated based on several metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), the percent standard error of the prediction (% SEP), and Coefficient of Determination (R^2) [1].

The key findings of the study are as follows:

- the LSTM model outperformed the other models in all time intervals in predicting the temperature and humidity, achieving the lowest MAE, RMSE, SEP, and the highest R-squared values;

- the increase in the time interval adversely affects the performance of the models;
- the DNN model performed better than the 1D-CNN model but not as well as the LSTM model;
- the performance of the models varied for different climate variables, with temperature being the easiest to predict and humidity being the most challenging.

These results provide insights into the effectiveness of time series deep learning models for climate prediction in indoor hydroponic greenhouses. The LSTM model outperformed the other models at shorter time intervals, whereas the DNN model showed the best performance at longer time intervals. Increasing the time interval from 1 to 15 min adversely affected the performance of the models. These findings can guide the development of intelligent control systems for indoor hydroponic greenhouses and contribute to the advancement of sustainable food production. Nevertheless, the study had some limitations. First, the dataset used in the study was limited to one week, which may not represent the long-term climate conditions in a hydroponic greenhouse. Second, the study only considered three deep-learning models. The other models may have better performance for climate prediction. Finally, the study did not consider external factors, such as weather conditions and plant growth, which might affect the climate conditions in the greenhouse.

2. Indoor Hydroponic Greenhouses

In recent years, there has been growing interest in applying time series deep learning models for climate predictions in various domains, including indoor hydroponic greenhouses [7][8]. These models can potentially capture the complex relationships between different variables and make accurate predictions based on historical data.

Deep Neural Networks (DNN) are a type of deep learning model that can learn complex nonlinear relationships between input and output data. DNN is used widely for climate predictions in various domains. DNN models are useful for predicting nonlinear systems because they can model such systems without making assumptions implicit in most traditional statistical approaches [9][10]. DNN models have several advantages over other nonlinear models because they can approximate a broad class of functions with high accuracy, making them universal approximators. These models have been used to forecast greenhouse climatic data with superior results to physical models [11][12][13]. On the other hand, there are some limitations to using DNN models, such as optimization issues, applicability to real-world problems, over-fitting, the need for many training sets, and poor stability in strongly coupled and complex systems [12]. Several studies have proposed time-series models to provide reduced representations of large numerical systems for an accurate simulation and prediction of the dynamic responses. Since Lapedes and Farber [14] combined a nonlinear time series model with DNN, this approach has attracted attention for integrating machine learning algorithms and regression models through methods, such as autoregressive moving average model (ARMAX), nonlinear autoregressive network (NARX), and autoregressive integrated moving average model (ARIMA). NARX is a class of dynamic DNN models applied widely in various fields because they can represent any nonlinear function based on the ARX input [15].

LSTM is a recurrent neural network (RNN) that can handle sequential data with long-term dependencies. LSTM is used widely for time series analysis and prediction in various domains. In climate predictions, LSTM has been applied to predict different variables, including temperature, humidity, and wind speed. Liu et al. [6] used an LSTM model to predict the temperature and humidity in a greenhouse. They compared the performance of the LSTM and RNN models and reported that the LSTM model outperformed the RNN model. Hu et al. [16] proposed a hybrid model that combined LSTM with a differential evolution algorithm for predicting wind speed. They reported improved accuracy compared to traditional statistical models.

CNN is a type of deep learning model that can learn spatial and temporal patterns in data. CNN is used widely for image and signal processing and shows promising results for time series analysis and prediction. In climate predictions, CNN has been applied to predict different variables, including temperature, humidity, and CO_2 concentration. For example, Jin et al. [17] applied a CNN and LSTM model to predict temperature, humidity, and wind speed. They reported that the CNN model showed better performance than traditional statistical models. Tzoumpas et al. [18] proposed a data-filling methodology and used CNN and LSTM models to predict indoor temperature. They reported improved accuracy compared to traditional statistical models.

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