

A Study on Web-based Real-time Greenhouse Crops Pest Diagnosis System using Artificial Intelligence

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Abstract: Background/Objectives: An effort to increase agricultural output is a very important factor in reducing the agricultural population. The convergence of ICT technology makes it possible to computerize and mechanize the cultivation of greenhouse crops, but the damage from disease and harmful insects is very serious, resulting in a decrease in production. Therefore, the diagnosis and prevention of pests are necessary, and studies on the pests prediction system using artificial intelligence have been conducted. In this paper, we propose a pests diagnosis system using web - based artificial intelligence.

Methods/Statistical analysis: It is a model to diagnose the correct name of pests through the characteristics of pests to minimize the damage caused by pests that may occur during the cultivation of greenhouse crops and to make appropriate initial responses. It is a situation that needs pre-diagnosis and prevention of pests, so we constructed a data set using the data on pests generated during the cultivation of red peppers among the professional data on pests registered in the national crop pest management system and learned the pests data through the TensorFlow.JS library. **Findings:** Since it is necessary to diagnose and prevent pests in advance, we proposed a web based artificial intelligence system to diagnose pests in real time and made it easy to enter and use data via JavaScript, allowing users to use a web browser instead of a console entry. This makes it possible to utilize the powerful functions provided on the web, use the system in an environment in which an internet connection is possible and handle the data entry and modification easily. We can improve the utilization of diagnostic results by using tools such as tables and graphs through a web browser, accumulate the data and results used in the diagnosis of pests by linking with the web based database and improve the accuracy by re-learning the model. Based on three diseases, the prediction model was tested five times, and the prediction model accurately diagnosed the disease through the input data. It was also found that it is possible to accurately predict the disease through the feature data of the disease even if there are some errors in the entry process. **Improvements/Applications:** Future studies should continue to be carried out to improve the response speed to analysis request and subdivision work for the feature information of a disease in order to exclude the possibility of errors in the diagnosis of pests when the feature data of the disease is similar.

Keywords: Artificial Intelligence, Pests, Node.JS, TensorFlow.JS,

I. INTRODUCTION

Our task is to increase agricultural production even if the

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number of people engaged in agriculture is gradually decreasing. In recent agriculture-related industries, computerization and mechanization of crop cultivation have been conducted due to the convergence of ICT technology. Especially, a lot of information about greenhouse cultivation is shared as the area of greenhouse cultivation is expanding. Since the production amount is often reduced due to various pests in the cultivation of greenhouse crops, however, it is necessary to accurately diagnose pests by the experts and to share information about the pests. In order to solve this problem, there are various studies on expert systems [1,2], and studies of applying the expert system, one of the artificial intelligence fields, to agriculture are spreading[3]. This paper proposes a model that can diagnose the accurate name of pests by using the artificial intelligence technology through the characteristics of pests occurring during the cultivation of crops to minimize damage through appropriate initial response. Various mobile devices that can use a web browser can diagnose pests in real time. Existing studies are limited to monitoring the air temperature and soil humidity through wireless communication environment in the cultivation facility, and studies of using the results analyzed with these data in limited places such as laboratories have been conducted, and it is difficult to apply them to the agricultural environment where analysis and diagnosis should be performed quickly. However, the proposed model has the advantage of improving the accuracy of the diagnostic system by entering simple feature information through a web browser, making a diagnosis through it and complementing the model in real time. It is expected that this diagnostic system will help to quickly diagnose pests, a major threat to the productivity of the cultivation of greenhouse crops and increase the agricultural production by the early response through accurate diagnosis.

II. RELATED WORK

2.1 Machine Learning

Machine Learning is a field of artificial intelligence which relates the problem of learning to a general inference concept in data samples [4,-6]. All learning processes of Machine Learning consist of two steps: First, it estimates the unknown dependency in the system from a given set of data. Second, it uses the estimated dependency to predict the new output of the system.



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The method of Machine Learning is divided into supervised learning and unsupervised learning. A set of learning data displayed in the supervised learning is used to estimate or map the input data to the desired output, and unsupervised learning has no concept of output during the learning process because labeled examples are not provided. In the supervised learning, this procedure can be considered as a classification problem because finding a group of input data or discovering a pattern can be determined by a learning plan or model. Classification refers a learning process in which data is classified into a set of finite classes. In general, the Machine Learning operation is regression and clustering. In the case of regression problems, the learning function maps data to actual value variables, and the value of the predictor variable can be estimated for each new sample [7]. Clustering is also a task to find a category or cluster to describe a data item, and new samples can be assigned to one of the identified clusters regarding similar characteristics.

2.2. Node.JS

Node.js is a software platform used to develop scalable network applications (server side). As a latest framework to implement event models through the entire stack, the architecture as single-threaded server-side JavaScript environment implemented in C and C++ is easy to use because it is composed of a functional and expressive language [8]. In addition, as a core JavaScript module designed to support interaction with the Google V8 JavaScript engine and host OS, V8 uses JIT compiling to greatly outperform the existing interpreter-based approach and has high throughput through a single-threaded event loop. The following [Figure 1] is an example of code that simply creates an HTTP server. It can be created simply through node.js core library and responds with an HTML page for every request. Each time the server receives an incoming HTTP request, the lambda function provided in `createServer` method is called with the associated HTTP request and response object [9].

```
var http = require('http');
http.createServer(function (req, res) {
  res.writeHead(200, {'Content-Type': 'text/html'});
  res.end("<!doctype html><html><body><p>Hello World</p></body></html>");
}).listen(3000, '127.0.0.1');
```

Figure 1: Simple Creation of a HTTP Server

2.3. TensorFlow

Although there are many tools and frameworks to train neural networks, Google's TensorFlow is the most widely used framework [10]. TensorFlow also supports various models, including different types of learning algorithms. The TensorFlow model is a data flow graph that represents calculations, and the nodes of the graph mean various operations. It includes mathematical functions such as matrix multiplication and addition, and can do constants, random operations, sequences for initializing the Tensor values, log event generation for debugging, and variable operations [11]. In TensorFlow, a variable is a special kind of operation that returns a handle for a tensor. It can be said that the tensor has a variable, and the variable operation can be also combined

with the result handle. This handle can be passed as a factor to operations that read or update the tensor [12]. Recently, Google has added TensorFlow.js, a WebGL acceleration library that enables learning and execution of the Machine Learning model in a web browser, which includes the function to load and use the learned model in the Keras API, regular tensorflow and can run the neural network quickly on the client's GPU [13].

III. PROPOSED SYSTEM

This study is about the web - based artificial intelligence pest diagnosis system to diagnose pests in real time by using the js. Tensorflow library, the JavaScript version of TensorFlow designed to use TensorFlow, an open source-based machine learning framework in Node.js or web browsers. The web-based AI diagnostic system via JavaScript has three major advantages in entering and using data: First, users can take advantage of the powerful functions provided on the web by not using the console to input data, but using the web browser they use frequently. In particular, the system can be used in any environment where the internet connection is possible, data entry and correction are easy, and input forms can be easily changed. Second, the data can be provided to users in real time using a tool such as tables or graphs via a web browser, thereby improving the utilization of the diagnostic result. Third, when it is used it in conjunction with a web-based database, it is possible to improve the accuracy of the model that accumulated the result and data used for diagnosis through re-learning.

3.1. System Configuration

The following [Figure 1] is a block diagram of the proposed system. A web-based pest diagnosis system using artificial intelligence consists of a data entry / output process, a diagnostic process and a storage process. Data entry / output is performed through a UI (User Interface) created using HTML (Hyper-Text Markup Language). The data entered by the user is entered through a predefined input form in order to improve the convenience of the entry and the accuracy of the diagnosis. Diagnostic result values are also provided to the user through HTML. Data entered by the user is defined as categorical data such as the season in which the pests occur, the shape and occurrence site of the lesion and continuous data such as temperature, humidity, soil acidity.

The following is the data diagnosis step, allowing the user to diagnose the value using the input data based on the pre-built data set. The diagnostic result value is provided to the user through a web page. The last is the data storage step. Both the entered data and the diagnostic result value are stored in the database. Diagnostic values are used to verify the data and update existing data sets to improve the accuracy of the model.



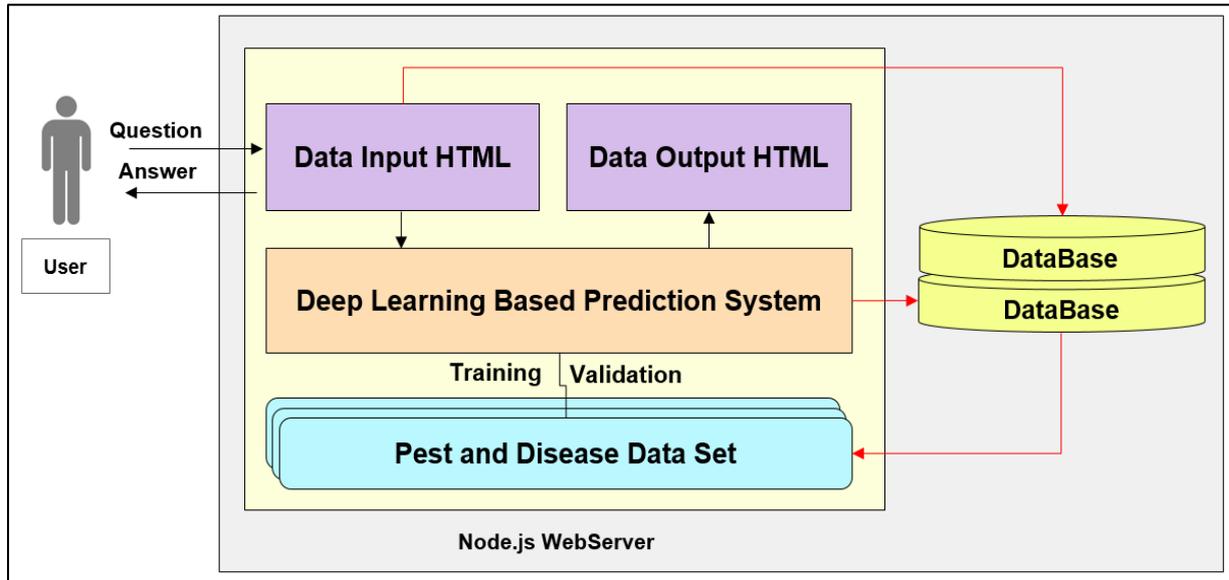


Figure 1: System Configuration

IV. TEST AND RESULT

In this study, the basic data used for the diagnosis of pests is the data on pests generated during the cultivation of red peppers among the professional data on pests registered in the

national crop pest management system. Data on red pepper pests created the primary classification code as shown in [Table 1] depending on the types of pests

Table 1: Primary Classification Code

Classification	Food Crops	Fruit Tree	Vegetable	Flowering plant	Special Crops	Weeds
Hierarchical Classification	C01	C02	C03	C04	C05	C06

Red peppers used in this study are classified as vegetable and have C03 as the primary classification code. The

following [Table 2] is the secondary classification code that classifies the codes of vegetable crops.

Table 2: Secondary Classification Code

Crop Name	Code	Crop Name	Code	Crop Name	Code
Eggplant	C0301	Leaf Mustard	C0302	Hot Pepper	C0303
Horseradish	C0304	Ragwort	C0305	Carrot	C0306
Codonopsis lanceolata	C0307	Strawberry	C0308	Garlic	C0309

The second classification code of red peppers was classified as C0303. [Table 3] below shows some data of the tertiary classification code (Season, Environment, Part of Origin) classified by some characteristics of pests occurring in red peppers, and the following [Table 4] is the tertiary classification code (Symptom, Infection Color).

For example, among the diseases occurring in red peppers (C0303), phomopsis blight appears mainly in summer and occurs in the environment of high temperature and humidity. The onset occurs mainly in leaves, petioles, fruit stalks and branches. Symptoms include leaf blight and fallen leaves. In addition, PH of soil, temperature/ humidity information and the type of disease are separated to write the features of the disease and create a model through learning.

Table 3: Example of Tertiary Classification Code(Season, Environment, Part of Origin)

Code	Pest Name	Season	Environment				Part of Origin					
			High Temp.	Low Temp.	D r y	High Humidity.	Leaf	Petiole	Fruit Stalk	Bough	Stem	Fruit
P01	Cercospora leaf spot	2	1	0	0	1	1	1	1	1	0	



P02	Black mold	2	1	0	0	0	0	0	0	0	0	1
P03	Black dot fruit rot	2	0	0	0	0	0	0	0	0	0	1
P04	Alternaria leaf spot	0	1	0	0	1	1	0	0	0	0	0
P05	Bacterial canker	0	0	0	0	0	0	0	0	0	0	0
...

Table 4: Example of Tertiary Classification Code(Symptom, Infection Color)

Code	Pest Name	Symptom						Infection Color
		Rot	Soft Rot	Leaf Blight	Fallen Leaves	Fruit Drop	Necrosis Blister	
P01	Cercospora leaf spot	1	1	0	0	0	0	0
P02	Black mold	1	0	0	1	0	0	1
P03	Black dot fruit rot	0	0	0	0	0	0	2
P04	Alternaria leaf spot	1	0	0	0	0	0	3
P05	Bacterial canker	0	0	0	0	1	1	4
...

The feature information created as shown in [Table 3] and [Table 4] is learned using js.tensorflow. To learn the model of the proposed system, the learning rate was set to 0.01 and it was learned 500 times. The learning result loss ratio was 0.00029. The learned model is used to diagnose what kind of disease is the input data, and the diagnostic result provides the user in a probability form of the disease which shows a high agreement with the feature information entered by the user using the softmax technique.

Based on P01(Cercospora leaf spot), P02(Black mold) and P03(Black dot fruit rot) among the three diseases in the classification codes of [Table 3] and [Table 4], the experiment of the proposed system changed and entered some data from the data entry page in [Figure 2] below to test the prediction model 5 times and then tested how to predict diseases.

Query Code

Season	<input type="radio"/> (0) No <input type="radio"/> (1) Spring <input type="radio"/> (2) Summer <input type="radio"/> (3) Autumn <input type="radio"/> (4) Winter
Environment	<input type="radio"/> (0) No <input type="radio"/> (1) High Temp. <input type="radio"/> (2) Low Temp. <input type="radio"/> (3) Dry <input type="radio"/> (4) High Humidity
Part of Origin	<input type="radio"/> (0) No <input type="radio"/> (1) Leaf <input type="radio"/> (2) Petiole <input type="radio"/> (3) Fruit Stalk <input type="radio"/> (4) Bough <input type="radio"/> (5) Stem <input type="radio"/> (6) Fruit
Symptom	<input type="radio"/> Rot <input type="radio"/> Soft Rot <input type="radio"/> Leaf Blight <input type="radio"/> Fallen Leaves <input type="radio"/> Fruit Drop <input type="radio"/> Necrosis Blister
Infection Color	<input type="radio"/> (0) No <input type="radio"/> (1) Black <input type="radio"/> (2) yellowish brown <input type="radio"/> (3) taupe <input type="radio"/> (4) buff <input type="radio"/> (5) White <input type="radio"/> (6) greenish brown <input type="radio"/> (7) brown <input type="radio"/> (8) dark brown

Figure 2: Web Page for Data Entry

As shown in the following [table 4], the prediction model accurately diagnosed the disease through the input data. This demonstrated that the disease can be accurately predicted through the feature data of the disease even if there are some errors in the entry process. However, it was found that there is a possibility of misdiagnosis if the feature data of the disease is similar, and it is necessary to work on the feature information segmentation of the disease to solve this problem and to improve the response speed to the analysis request.

Table 4: Experiment Result

No	CODE	Test Data	Test Result
1	P01 P02 P03	[2,1,0,1,1,1,1,1,0,0,1,1,0,0,0,0,0,1] [2,1,0,1,0,0,0,0,0,0,1,1,0,0,1,0,0,0,0,1] [2,0,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,0,3]	0.9986324, 2e-7, 0.0001697, 0.0010642, 0.0001332 1e-7, 0.9994165, 0.0001209, 0.0004597, 0.0000031 0.0004476, 0.0010908, 0.9972867, 0.0000074, 0.0011675



2	P01 P02 P03	[2,1,0,0,0,1,1,1,0,0,1,1,0,0,0,0,0,1] [1,1,0,0,0,0,0,0,0,1,1,0,0,1,0,0,0,0,0] [2,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,2]	0.9951575, 0.0000012, 0.0037601, 0.0005973, 0.0004836 6e-7, 0.9975958, 0.0000649, 0.0023314, 0.0000075 0.0045696, 0.0023203, 0.9925099, 0.0000666, 0.0005335
3	P01 P02 P03	[2,1,0,0,1,1,1,1,0,0,1,1,0,0,1,0,0,0,0] [3,1,0,0,0,0,0,0,0,0,1,1,0,0,1,1,0,0,0,1] [2,0,1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,2]	0.9986919, 2e-7, 0.0005059, 0.0005358, 0.0002663 0.0000013, 0.9907117, 0.0091201, 0.0001364, 0.0000303 0.0006245, 0.0012335, 0.9978617, 0.0000057, 0.0002746
4	P01 P02 P03	[2,1,0,0,1,1,1,1,0,0,1,1,0,0,0,1,0,0,0] [1,1,0,0,0,0,0,0,0,0,1,1,0,0,1,0,0,0,0,1] [2,0,0,1,0,0,0,1,0,0,1,0,0,0,0,0,1,0,0,2]	0.9984272, 3e-7, 0.0004384, 0.0008715, 0.0002627 3e-7, 0.9966763, 0.0000426, 0.0032702, 0.0000106 0.0033284, 0.000469, 0.9879209, 0.0000157, 0.0082661
5	P01 P02 P03	[2,1,0,0,1,1,1,1,0,0,1,1,0,0,0,0,0,0,0] [2,1,0,0,0,0,0,0,1,0,1,1,0,0,1,0,0,0,0,1] [3,0,0,1,0,0,1,0,0,0,1,0,0,0,0,0,0,0,2]	0.9994223, 1e-7, 0.0002298, 0.0003078, 0.0000399 0.0000278, 0.9900246, 0.0080732, 0.0018174, 0.0000572 0.0002457, 0.0000299, 0.9996873, 1e-7, 0.000037

V. CONCLUSION

The task of reducing manpower engaged in agriculture and increasing agricultural production is emerging as issues in our society. Recently, ICT technology has been integrated into agriculture to computerize and mechanize the cultivation of crops. However, there are only a few systematic studies on the pre-diagnosis and prevention of pests, requiring sharing information about pests. Thus, we propose a real - time analysis system model operating on the web by using tensorflow.js, a JavaScript - based artificial intelligence framework, and it is a model that can be used for the diagnosis of pests in the cultivation of red peppers. The features of JavaScript-based artificial intelligence system are as follows: It operates only with a relatively simple installation process, the Internet is connected such as a computer or smart phone, data can be entered on any device where a browser is running via a web browser, which enables the analysis and diagnosis of pests. In addition, the JavaScript-based AI analysis system can be implemented in JavaScript and HTML, so developers can concentrate only on Machine Learning itself without having to learn a separate language for artificial intelligence. Based on these advantages, it is possible to lower the entry barriers of developers, which makes it possible to implement diagnosis and prevention systems for a wide range of pests. Future studies should continue to be carried out to improve the response speed to analysis request and subdivision work for the feature information of a disease in order to exclude the possibility of errors in the diagnosis of pests when the feature data of the disease is similar.

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