Diagnosis of Fruit Tree Diseases and Pests Based on Agricultural Knowledge Graph

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Abstract. In order to realize the accurate prediction of fruit tree diseases and pests in the text description, this paper combines knowledge graph, representation learning, deep neural network and other methods to construct a fruit tree disease and pest’s diagnosis model. The model first constructs a knowledge graph in the agricultural field, and encodes the knowledge in the agricultural field through the knowledge representation model, combines the description text provided by the user to obtain the representation vector of the fruit tree diseases and pests feature entity, and then passes the representation vector and the pest image representation vector through CNN-DNN-BiLSTM network recognizes fruit tree diseases and pests. Three kinds of diseases and pests of apple trees were selected in the experiment: Apple Ring Rot, Apple Scab and Adoxophyes orana. Compared with the VGG network and the BiLSTM network, the precision rate of the model in this paper has been improved by 19%, 4%, 3%, 20% and 25%, 2% on Apple Ring Rot, Apple Scab and Adoxophyes orana, respectively. It can fully integrate agricultural knowledge graph and deep learning technology, and play a positive role in improving the diagnosis of fruit tree diseases and pests.

Keywords: knowledge graph, representation learning, deep learning, fruit tree diseases and pests.

1. Introduction
Knowledge graph is a technical method that uses graph models to describe the relationship between knowledge and modeling the world [1]. The knowledge graph consists of nodes and edges. Nodes can be entities, such as a person, a book, etc., or abstract concepts, such as artificial intelligence, knowledge graphs, etc. Edges can be attributes of entities, such as names, book titles, or relationships between entities, such as friends and spouses. The earliest application of knowledge graphs is to improve the capabilities of search engines. Subsequently, the knowledge graph demonstrated rich application value in assisting intelligent question and answering, natural language understanding, big data analysis, recommendation calculation, Internet of Things device interconnection, and interpretable artificial intelligence. Smart agriculture is a more in-depth and hotter field in the application of knowledge graphs. Knowledge graphs have good performance in agricultural intelligent question and answer, agricultural knowledge retrieval, and auxiliary pest control.
In smart agriculture, the diagnosis and control of fruit tree diseases and pests has always been a problem that agricultural experts and fruit growers are very concerned about. However, due to the wide variety of diseases and pests and complex disease characteristics, it is difficult for others to identify except for experienced experts or fruit growers, and the diseases and pests have seriously affected the yield of fruit trees. Therefore, the intelligent identification and control of fruit tree diseases and pests has always been a key and difficult problem faced by agricultural personnel. Since the diseases, symptoms, control measures and other agricultural entities involved in fruit tree diseases and pests are complicated, knowledge graph technology will play a positive role in this. Therefore, this paper proposes a fruit tree disease and pest's diagnosis model based on knowledge graph. Representation learning is used to combine knowledge graph and deep learning, and by supplementing the information about the relationship between the pest entities and the symptom entities described by users and the entities in the agricultural knowledge graph, the precision rate of pest identification is improved.

2. Related Work
In recent years, the research and application of large-scale knowledge graphs has received widespread attention in many fields such as agriculture, medical biology, finance and insurance. Typical examples include Google's launch of Google Knowledge Graph [2] in 2012, Facebook's graph search, Microsoft Satori, etc. The most representative large-scale network knowledge acquisition work includes DBpedia, Freebase, KnowItAll, WikiTaxonomy and YAGO, as well as BabelNet, ConceptNet, DeepDive, NELL, Probase, Wikidata, XLOre, Zhishi.me, etc. Among them, knowledge graphs in the agricultural field are also emerging. Qi Chenglin et al. [3] proposed a method for constructing China's meteorological and agricultural knowledge graph based on semi-structured data. Yuanzhe Chen et al. [4] proposed a method to automatically identify agricultural entities from unstructured text and connect them to form a knowledge graph, and use the knowledge graph to conduct agricultural knowledge retrieval and question answering.

Aiming at the diagnosis of fruit tree diseases and pests, artificial intelligence technology is playing a huge advantage. The latest development of deep neural networks enables researchers to greatly improve the accuracy of target detection and recognition systems. Alvaro Fuentes et al. [5] proposed a method based on deep learning to detect tomato plant diseases and pests. By collecting tomato pests and diseases images with different resolutions and using deep learning network models such as VGG to identify diseases and pests, 9 different types of diseases and pests can be accurately identified. Weilu Li et al. [6] proposed an improved ZF network model, which uses self-learning saliency feature mapping to locate and count agricultural pests in images, with an accuracy rate of 93%. Ahmad Arib Alfarisy et al. [7] used four different languages to search for images of rice pests and diseases, and used CaffeNet to identify them, which had obvious effects on the identification of rice pests and diseases, with an accuracy rate of 87%. Although the above methods have a certain effect in the identification of pests and diseases, only image data is considered, so the accuracy rate needs to be improved.

The prevention and control of fruit tree diseases and pests is a key issue in the agricultural field. Accurate and faster detection of fruit tree diseases and pests can help develop early treatment techniques while greatly reducing economic losses. This paper aims at this problem, combining agricultural knowledge graph and deep learning. According to the entity information related to the pests and diseases in the agricultural knowledge graph, the related entities in the text provided by the user are extracted to enrich the characteristics of the pests and diseases, and then learn through the deep neural network model together with the pest images. Finally, the disease and pests are diagnosed.

3. Knowledge Representation Learning Model
The traditional knowledge graph represents a knowledge in the form of triples \((h, r, t)\), where \(h\) represents the head entity, \(t\) represents the tail entity, and \(r\) represents the relationship. With the development of deep learning technology, the representation of knowledge in the knowledge graph
hopes to map entities and the relationships between entities to a continuous low-dimensional space to improve the shortcomings of the original triples that are difficult to calculate. TransE, TransH and TransR models have achieved excellent results in knowledge representation learning models. TransE model [8] regards the relationship as the translation vector \( \hat{r} \), so that the head and tail entity vectors satisfy the Equation (1).

\[
\hat{h} + \hat{r} \approx \hat{t}
\]  

(1)

Its loss function is shown in Equation (2).

\[
f_r(h, t) = \|\hat{h} + \hat{r} - \hat{t}\|_2^2
\]

(2)

TransE model is simple in form, easy to calculate, and has strong scalability. At the same time, it also has certain shortcomings, and it is less effective when dealing with one-to-many relationships or reflexive relationships. In order to improve TransE’s shortcomings in dealing with complex relationships, extended models of TransH and TransR are proposed.

TransH model [9] also uses two vectors to represent the entities \( \hat{h} \) and \( \hat{t} \). The difference is to distinguish the relationships and entities in the knowledge graph. TransH expresses the relationship as two vectors: the normal vector of the hyperplane \( \hat{w}_r \) and the vector of the relationship \( r \) in the hyperplane express \( \hat{d}_r \). Its loss function is shown in Equation (3).

\[
f_r(h, t) = \|\hat{h} + \hat{r} - \hat{t}\|_2^2
\]

(3)

Among them, \( \hat{h}_r = \hat{h} - \hat{w}_r^T \hat{h}\hat{w}_r \), \( \hat{t}_r = \hat{r} - \hat{w}_r^T \hat{t}\hat{w}_r \), at the same time make \( \|\hat{w}_r\|_2 = 1 \).

TransR model [10] is based on the TransE and TransH models, projecting the relational vector to different spaces. It has a good performance in the knowledge graph of complex relationships, so this paper uses the TransR model for knowledge representation. TransR model assigns a mapping matrix \( M_r \in R^{d \times d} \) to each relationship in the knowledge graph, and its loss function is shown in Equation (4).

\[
f_r(h, t) = \|\hat{h}_r + \hat{r} - \hat{t}_r\|_2^2
\]

(4)

Among them, \( \hat{h}_r = \hat{h} M_r \), \( \hat{t}_r = t M_r \).

4. Model Architecture

The diagnosis model of fruit tree diseases and pests based on agricultural knowledge graph proposed in this paper. The core idea is to use user-provided diseases and pests feature description text and the triples in the knowledge graph to get the associated symptom entity, and then combine the diseases and pests’ images to jointly construct a neural network based on deep learning to realize the diagnosis of diseases and pests.
The framework of the diagnosis model of fruit tree diseases and pests based on the agricultural knowledge graph is shown in Figure 1. It is mainly divided into four parts:

![Model Flow Chart](image)

**Figure 1. Model Flow Chart.**

1. The agricultural corpus is obtained through web spiders and manual collection, and the agricultural knowledge graph is constructed. At the same time, change its form into a trainable triple form, and use the knowledge representation model training to obtain the representation vector of the entity in the agricultural knowledge graph;
2. Obtain user data, including description text and images of fruit tree diseases and pests;
3. Obtain the symptom entity in the text according to the relationship between the pests and symptoms in the agricultural knowledge graph;
4. The symptom entities and the images of diseases and pests are used as the input of the CNN-DNN-BiLSTM model to construct a classifier to obtain the diagnosis results of fruit tree diseases and pests.

In this paper, the proposed model is referred to as CDBLR model, namely CNN-DNN-BiLSTM-TransR model. Its meaning is a diseases and pests diagnosis model based on TransR representation learning combined with CNN-DNN-BiLSTM dual-channel neural network.

5. **Detailed Process**

According to the above framework, the specific process of the diagnosis model of fruit tree diseases and pests based on the agricultural knowledge graph consists of three parts, as shown in Figure 2. Among them, the right is the main process of the diagnosis model, the upper left is the use of knowledge graphs to obtain symptom entities, and the lower left is the text feature extractor for the description of diseases and pests. The input of the model is user data, which is divided into pest images and description text. For image data, the model uses the CNN-DNN network to extract features and obtain a low-dimensional representation vector. For the description text data, extract the associated symptom entities in the text according to the constructed agricultural knowledge graph, and use the knowledge representation model to obtain the representation vector of the entity to form the entity matrix $E^{m \times k}$, and then extract the description text features through the BiLSTM network. Finally, the image data vector and the description text data vector are fused and sent to the softmax classifier to diagnose diseases and pests.
5.1. Symptom Vector of User Description Text

As some fruit tree diseases and pests have unobvious characteristics, it is difficult to identify them only by images. The user's description of pests and diseases more or less contains information about the characteristics of diseases and pests. Using the symptom description text to dig out the hidden characteristics of diseases and pests will help to accurately judge the diagnosis of pests. Therefore, this paper will use the user's pest description information, through the semantic description of text and knowledge, find relevant pest entities in the knowledge graph.

The specific processing process is shown in the upper left of Figure 2. This paper will first construct an agricultural knowledge graph based on agricultural knowledge and convert the original agricultural knowledge information into a triple form, such as "Ring Rot, Symptom, Round Brown Spot", "Ring Rot, Symptom, Soft Rotten", etc. The triples will be stored in the graph database as a basis for further query.

Then the knowledge representation is carried out through TransR model, and the constructed agricultural knowledge graph data is used as the input of the representation model. The representation model uses $h + r \approx t$ as the basic idea to map entities and relationships into low-dimensional space. The embedded representation of knowledge is shown in Figure 3. Taking into account the complexity of the agricultural knowledge graph, TransR model realizes the distinction between entities and relationships. At the same time, for different semantic spaces, the entities are projected to the vector space of the knowledge representation model relationship shown in Figure 3, so that the many-to-many relationship has a more accurate vector representation. For example, for the relational symptom $r$, a mapping matrix $M_r \in \mathbb{R}^{k \times d}$ is assigned to it, so that the Ring Rot vector $\tilde{h}$ and the Round Brown Spot vector $\tilde{i}$ can obtain their projection vectors $\tilde{h}_r$ and $\tilde{i}_r$ through $\tilde{h}M_r$ and $\tilde{t}M_r$.

According to Equation (4), the vector representation $e^h_R$ of the Ring Rot entity was obtained. Once the knowledge representation is complete, it can be used to calculate and discover symptom entities in the descriptive text. The example shown in the upper left of Figure 2. Then, according to the trained entity representation vector $e^h$, the entity matrix $E^{text}$ describing the text can be formed, as shown in Equation (5).
Among them, $k$ is the dimension of the entity vector, and $m$ is the number of entities in the chief complaint.

\[
E^{m \times k} = [e^1, e^2, \cdots, e^m]
\] (5)

Figure 3. TransR Knowledge Representation Model.

An entity matrix $E^{m \times k}$ describing the text is taken as the input to the BiLSTM network, as shown in the lower left of Figure 2. The BiLSTM network is used for text feature extraction, and the output vector $\hat{h}_t$ of the last LSTM unit is selected as the description text feature vector, as shown in Equation (6).

\[
\hat{h}_t = BiLSTM(\hat{h}_{t-1}, E^{m \times k})
\] (6)

5.2. Disease and Pest Image Feature Vector

The characteristic images of diseases and pests are photos of fruit trees provided by users when diseases and pests occur. The specific processing process is shown on the right side of Figure 2. The image of diseases and pests should be preprocessed and its size should be unified as 256*256, and it should be converted into a three-dimensional matrix $M_p$. Image features were extracted from CNN-DNN model to obtain a low-dimensional vector $P_z$.

5.3. Fusion of Text Feature Vectors and Image Feature Vectors

In Section 5.1, the characteristics of description text of disease and pests are extracted through the BiLSTM network, and the description text representation vector $\hat{h}_t$ is obtained. In Section 5.2, the image representation vector $P_z$ is obtained through the processing of image data of disease and pests through the CNN-DNN network. Finally, the description text representation vector $\hat{h}_t$ and image representation vector $P_z$ were fused, as shown in Equation (7), to obtain the final representation vector $p$ of patient information.

\[
p = \hat{h}_t + P_z
\] (7)

Finally, the representation vector is calculated according to Equation (7), and the softmax classifier is used to obtain the diagnosis results of diseases and pests, as shown in Equation (8).
\[ f(p) = Wp + b \]  \hspace{1cm} (8)

6. Experiments

6.1. Data Source
The experiment will verify the model in this paper through the diagnosis of three apple diseases and pests. The data includes two parts: one is the agricultural data used to construct the agricultural knowledge graph. It comes from www.nongyebaike.cn and contains 24,360 pest-related entities and 8 relationships (belonging to, commonly used pesticides, aliases, images, control methods, pathogens, disease symptoms, and related resources) and 126,350 triple relationships. The other part of the data is the image data of pests and diseases, which are collected manually and automatically by web spiders, totaling 5390 images.

6.2. The Design of Experiments
This paper is developed based on PyTorch and TensorFlow deep learning frameworks, and the model in this paper is designed to compare with the following models for result analysis.

Compared with related models, the CDBLR model proposed in this paper is mainly by adding the information of agricultural knowledge graph to the traditional BiLSTM text classification model, so BiLSTM is an important reference model. In addition, this article also relates to the image classification model. VGG network has a good performance in image classification and can be used as another important reference model.

In this paper, through the cross-validation method, each experiment randomly selects 70% of the data as the training set, 30% of the data as the test set, and repeats 10 times to take the average as the final result. This paper uses precision rate, recall rate and F1 value as evaluation indicators.

6.3. Experimental Results and Analysis
In this paper, the CDBLR model is compared with other models on apple diseases and pests. The precision rate results are shown in Table 5, the recall rate results are shown in Table 6, and the F1 value is shown in Table 7. The common Apple Ring Rot, Apple Scab and Adoxophyes Orana were selected as the diagnostic objects.

### Table 1. Comparison of precision rate of different models.

| Model | Apple Ring Rot | Apple Scab | Adoxophyes Orana |
|-------|----------------|------------|------------------|
| BiLSTM| 0.69           | 0.79       | 0.52             |
| VGG   | 0.84           | 0.62       | 0.75             |
| CDBLR | 0.88           | 0.82       | 0.77             |

### Table 2. Comparison of recall rate of different models.

| Model | Apple Ring Rot | Apple Scab | Adoxophyes Orana |
|-------|----------------|------------|------------------|
| BiLSTM| 0.75           | 0.83       | 0.63             |
| VGG   | 0.86           | 0.62       | 0.81             |
| CDBLR | 0.92           | 0.76       | 0.78             |

### Table 3. Comparison of F1 value of different models.

| Model | Apple Ring Rot | Apple Scab | Adoxophyes Orana |
|-------|----------------|------------|------------------|
| BiLSTM| 0.72           | 0.81       | 0.57             |
| VGG   | 0.85           | 0.62       | 0.78             |
| CDBLR | 0.90           | 0.79       | 0.77             |
By comparing Table 1, Table 2 and Table 3, it can be found that the CDBLR model proposed in this paper has good performance in Apple Ring Rot and Adoxophyes Orana. After the addition of the agricultural knowledge graph, the precision rate of the model is increased by 4%, 20% and 2%, the recall rate is increased by 6% and 14%, and the F1 value is increased by 5% and 17%, respectively, compared with the single VGG network. It shows that the entity information extracted from the description texts of diseases and pests in this paper has played a good role in the classification model. Because the description of symptoms in the user's description text is usually directly related to the diseases and pests produced by fruit trees, the model in this paper obtains the vector representation of the entity through the relationship of the triples in the agricultural knowledge graph. As the result of knowledge representation, the pest entity vector and its related symptom vector have a closer spatial relationship, so it will play a good role in the classification model. At the same time, compared with BiLSTM and VGG, the model in this paper has better performance in precision rate, recall rate and F1 value, and has a significant improvement in classification performance.

However, it can also be seen from the results that the model in this paper performs poorly in judging Apple Scab. After researching the data and knowledge graph, it is found that in the agricultural knowledge graph constructed, the description of the symptoms of Apple Scab and its related entities is relatively missing, and there are fewer images collected, so the desired effect is not achieved. This result also illustrates the role of the knowledge graph, and only a complete knowledge graph can be constructed to obtain a good identification and diagnosis result.

7. Conclusions
Aiming at the problem of difficult identification of fruit tree diseases and pests in agriculture, this paper proposes a deep neural network model based on agricultural knowledge graph to diagnose fruit tree diseases and pests, so that the diagnosis of diseases and pests is not only connected with the images of the diseases and pests, but also can be combined with the description text of the diseases and pests. Based on the construction of the agricultural knowledge graph, TransR model is selected as the knowledge representation of the low-dimensional embedded knowledge graph. Then the model combines the relationship in the agricultural knowledge graph and the description text information of the disease and pests to obtain the symptom description text representation vector. Combining the image data of diseases and pests, BiLSTM network and CNN-DNN network are used to extract the description text feature and image feature, and finally they are fused to obtain a relatively complete diseases and pests feature, so as to diagnose the diseases and pests. Experiments show that the model in this paper is better than traditional diagnostic methods in precision rate, recall rate, and F1 value. It proves that the agricultural knowledge graph entity added to the pest information has played a greater role in classification, showing the excellent classification performance of the auxiliary diagnosis model based on the agricultural knowledge graph. However, the model in this paper needs to be carried out on a relatively complete knowledge graph. At the same time, due to the complexity of agricultural knowledge, the colloquialization and diversity of terms, it will affect the accurate identification of symptom entities. This is also a problem that needs to be explored in further research in the future.

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