Algorithms for plant disease diagnostics by leaf image

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Abstract. This article discusses the task of detecting diseases of cultivated plants. When determining the phytosanitary status of cultivated plants, images of their leaves are considered as initial data. To solve the problem under consideration, a model of diagnostic algorithms based on two-dimensional threshold functions is proposed. The main idea of the proposed algorithms is to form a set of preferred diagnostic features and make decisions aimed at making a diagnosis based on a comparison of these features. The classification stages of the diagnostic algorithm model are presented. An assessment of the applicability of the proposed model is demonstrated using the example of solving the problem of diagnosing wheat diseases by leaf images.

Keywords: diagnostic algorithms, basic image slices, diagnostic features, preferred features, calculation of the overall score.

1 Introduction

In recent years, the tasks of creating and using information systems and technologies in agricultural production have become one of the main factors in the advancing of innovative and research and technical developments in this area. One of the main tasks of using modern information technologies is related to the creation of computer systems designed to diagnose crop diseases and predict their development.

In recent years, a number of research papers devoted to the diagnosis of plant diseases, in particular [1-6], have appeared. The problem of creating a computer system based on processing of images of cultivated plant leaves, which is intended for diagnosing diseases of their fruits, is considered. The introduction of automated diagnostic systems makes it possible to use unbiased information on the diagnosis of cultivated plants, to diagnose plant diseases in a timely and sufficiently accurate manner. This creates conditions for making decisions on plant protection measures [5, 6]. Image recognition methods and algorithms play a key role in the creation of computer systems designed to diagnose plant diseases.

An analysis of scientific sources on pattern recognition, in particular [7–20,32], shows that by now a number of recognition models have been created and rather well studied.
2 Statement of the problem
3 Proposed solution method

Formation of basic parts of leaf images

k = h × w, d_h = [h / h_k], w = [w / w_k] + d_w, d_h = \{0, if h \div h_k = 0\}, d_w = \{0, if w \div w_k = 0\}

Identification of a set of diagnostic features by leaf images
Identification of subsets of strongly connected diagnostic features. A system of “unrelated” subsets of diagnostic features is determined (separately for each space $\Theta$) for each image $\eta$. A set of “mutually unrelated” subsets $\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_n$ is formed. Let $\mathcal{S}_i \in \llbracket \mathcal{L} \rrbracket$. The system $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2 \cup \cdots \cup \mathcal{S}_n$ is the greatest system of subsets of diagnostic features. The measure of proximity estimates between subsets of diagnostic features. Let us assume that $n' < n$. Then the obtained set of features $\mathcal{S}' = \{\mathcal{S}_1', \mathcal{S}_2', \ldots, \mathcal{S}_n'\}$.

Identification of representative diagnostic features. Determination of preferred diagnostic features is based on the superiority of the feature in question when dividing the space of features. As diagnostic features of an image, in addition to features of the plant leaves, works [29, 30]. At this stage, a set of representative diagnostic features is considered, i.e., $\mathcal{C} = \{\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_n\}$. The main idea of determining preferred diagnostic features is based on the superiority of the feature in question when dividing the space of features. The entropy calculated for all slices $\mathcal{D}_j$ can be determined in different ways, for example, by the average distance between the elements of these subsets [28]. This measure of proximity is calculated the features $\mathcal{S}_i \cup \mathcal{S}_j \cup \mathcal{S}_k$. For example, the entropy calculated for all slices $\mathcal{D}_j$ can be determined in different ways, for example, by the average distance between the elements of these subsets [28]. The cardinality of the subset $\mathcal{S}_i$ is determined and denoted as $\Pi_{ij}$. As diagnostic features of an image, in addition to features of the plant leaves, works [29, 30].

At that time, each space $\mathcal{C}_{ij} = \mathcal{S}_i \cup \mathcal{S}_j \cup \mathcal{S}_k$. As diagnostic features of an image, in addition to features of the plant leaves, works [29, 30]. The main idea of determining preferred diagnostic features is based on the superiority of the feature in question when dividing the space of features. The entropy calculated for all slices $\mathcal{D}_j$ can be determined in different ways, for example, by the average distance between the elements of these subsets [28]. This measure of proximity is calculated the features $\mathcal{S}_i \cup \mathcal{S}_j \cup \mathcal{S}_k$. For example, the entropy calculated for all slices $\mathcal{D}_j$ can be determined in different ways, for example, by the average distance between the elements of these subsets [28]. The cardinality of the subset $\mathcal{S}_i$ is determined and denoted as $\Pi_{ij}$.

\[ \Pi_{ij} = \left( \frac{m_1}{n} \frac{\sum_{j=1}^n \sum_{S \in \mathcal{D}_j} (a_i - a_{iu})^2}{\sum_{S \in \mathcal{D}_j} \sum_{S_i \in \mathcal{C} \mathcal{D}_j} (a_i - a_{iu})^2} \right) \]

\[ \Pi_{ij} = \left( \frac{m_1}{n} \frac{\sum_{j=1}^n \sum_{S \in \mathcal{D}_j} (a_i - a_{iu})^2}{\sum_{S \in \mathcal{D}_j} \sum_{S_i \in \mathcal{C} \mathcal{D}_j} (a_i - a_{iu})^2} \right) \]
Determination of the difference function \( d(\mathcal{L}_u, \mathcal{L}_v) \) between two leaf images \( \mathcal{L}_u \) and \( \mathcal{L}_v \). The following principle is used: “the greater the value of the difference between these images.”

\[
\mathcal{L}_u = (a_{u1}, \ldots, a_{un_0}) n \mathcal{L}_v = (a_{v1}, \ldots, a_{vn_0}).
\]

\[
\mathcal{R}(\mathcal{L}_u, \mathcal{L}_v) = \sum_{i=1}^{n_0} \nu_i (a_{ui} - a_{vi})^2.
\]

7. Formation of strongly connected subsets of images. At this stage, a system of “mutually unrelated” subsets of images is formed. Let us assume that \( \mathcal{S}_A \) is the system of all disjoint images \( \{\mathcal{L}_1, \ldots, \mathcal{L}_u, \ldots, \mathcal{L}_m\} \). All the images \( \mathcal{L}_1, \ldots, \mathcal{L}_m \) are formed:

\[
\mathcal{S}_A = \{\mathcal{G}_1, \ldots, \mathcal{G}_u, \ldots, \mathcal{G}_m'\}.
\]

\[
\bigcap_{u=1}^{m'} \mathcal{G}_u = \emptyset; \bigcup_{u=1}^{m'} \mathcal{G}_u = \mathcal{S}_A; m' = |\mathcal{S}_A|.
\]

\[
\mathcal{L}_u \cup \mathcal{L}_v \mathcal{C}_j (j = 1, k)
\]
8. Determination of representative images in each strongly connected subset.

\[ Q_1 = \{ G_u \mid \# G_u = 1 \}, Q_2 = \{ G_u \mid \# G_u = 2 \}, Q_3 = \{ G_u \mid \# G_u \geq 3 \}. \]

\[ m (m' < m) \]

9. Determination of the images \( L'_u \) and \( L \) in the two-dimensional subspace of preferred features.

\[ D_i \left( D_i = \{ t_{i_1}, t_{i_2} \} \right) \]

\[ d_i(L'_u, L) = \sum_{v=1}^{2} \xi_v (a_{u,v} - a_{i_v})^2 \]

\[ t_i(L'_u, L) = \begin{cases} 1, & \text{if } d_i(L'_u, L) \leq \varepsilon_i; \\ 0, & \text{if } d_i(L'_u, L) > \varepsilon_i. \end{cases} \]

10. Calculation of the proximity estimate of arbitrary image \( L \) by class \( D_j \) in the subspace \( D_i \).

\[ \phi_i(D_j, L) = \sum_{L'_u \in D_j} g_u t_i(L'_u, L), \quad \overline{D}_j = L' \cap D_j \]
11. Estimating the proximity of an image to a class over all subspaces. At this stage, the proximity of the image $𝔏$ to the class $𝐷_𝑗$ ($𝑗 = 1, 𝑙$) is estimated. According to the 10th stage of this model, for each subspace $𝒟_𝑖$ of representative features, an estimate of proximity of the image $𝔏$ to the class $𝐷_𝑗$ ($𝑗 = 1, 𝑙$) was calculated. In this case, the final estimate of proximity of the image $𝔏$ to the class $𝐷_𝑗$ ($𝑗 = 1, 𝑙$) is determined as the sum of the total estimates obtained for all subspaces:

$$B(D_j, 𝜔) = \sum_{i=1}^{n'} y_i \phi_i(D_j, 𝜔),$$

where $y_u$ is the algorithm parameter ($i = 1, \ldots, n'$).

12. Decision rule. The decision is made for each element $[,] i.e.

$$β_{ij} = C(B(D_j, 𝜔)) = \begin{cases} 0, & \text{if } B(D_j, 𝜔) < c_1, \\ 1, & \text{if } B(D_j, 𝜔) > c_2, \\ Δ, & \text{if } c_1 \leq B(D_j, 𝜔) \leq c_2, \end{cases}$$

where $c_1, c_2$ is the algorithm parameter.

Thus, a model of diagnostic algorithms based on the construction of two-dimensional threshold functions is considered. Any algorithm $A$ in this model is completely determined by a set of parameters $𝜋$. The set of all diagnostic algorithms in the proposed model is denoted as $𝐴(𝜋, 𝜔)$.

The construction of the best diagnostic algorithm for the given problem is carried out in the space of parameters $𝜋$ by searching for its extreme values [27].

4 Experimental study

In order to test the capabilities of the diagnostic algorithms built by the developer, the task of diagnosing wheat leaf rust using leaf images is considered. It is known that rust of grain crops, especially wheat, is one of the most harmful and dangerous diseases in many regions of the world. The amount of damage and loss in the yield of wheat caused by this disease depends on a number of factors, for example, on the period of primary damage (that is, the stage of wheat development, the time of onset of the disease) and the intensity of the disease. Correct determination of the development stage is of great importance not only when studying harmful rust diseases, but also when conducting research to predict the development of diseases and organize protective measures for wheat in crop fields.

Wheat fields were photographed and baseline data was collected to diagnose wheat rust. A set of 300 images of wheat leaves was selected as the initial data. The number of possible diagnoses (that is, the phytosanitary status of wheat) is 2: 1) images of wheat leaves with yellow rust ($𝐷_1$); 2) images of wheat leaves without yellow rust ($𝐷_2$).

In the first part of the set ($𝐷_1$), there are 150 images. In the second part of the set ($𝐷_2$), there are also 150 images. The division of these images into training and control samples is shown in Table 1. To eliminate successful (or unsuccessful) division into equal parts, $t \times q$-fold cross-validation method was used [31].

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Training sample size</th>
<th>Control sample size</th>
</tr>
</thead>
<tbody>
<tr>
<td>$𝐷_1$</td>
<td>100</td>
<td>50</td>
</tr>
<tr>
<td>$𝐷_2$</td>
<td>100</td>
<td>50</td>
</tr>
<tr>
<td>Total</td>
<td>200</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 1. Dividing the source data into training and control samples.
Using this method, the data was divided into training and control samples as follows: the source images, or rather the vectors of features corresponding to them, were randomly divided into 30 equal parts (blocks). The number of images and the proportions of classes in each block are approximately equal. To eliminate successful (or unsuccessful) partitioning, 20 blocks will be included in the training sample and the remaining 10 ones will be included in the control sample. The diagnostic algorithm is trained on this sample, and the algorithm of the trained method is tested on the control sample (the remaining blocks). Based on the results of each test, an assessment of the quality of diagnostic algorithms based on the control sample is determined and collected. When performing each subsequent step, one block from the control and training samples is selected and exchanged. In this case, the attached blocks from the control sample are correspondingly separated so that they do not participate in the selection of candidates for inclusion in the training sample. This process is repeated until the access of all the blocks to the training and control samples has ceased, i.e., 30 times. The assessment of the quality of diagnostic algorithms is determined after the procedures of all iterations. The assessment of the quality of diagnostic algorithms is determined by the average values of all experiments and is simplified in descending order. This made it possible to express the results presented in tables 2 and 3 in natural numbers.

Decision making on the problem under consideration was carried out according to the following formula (similar to the formula for the decision rule in the model of Yu.I. Zhuravlev) [7]:

\[
\Psi(\mathcal{L}) = \begin{cases} 
1, & \text{if } \mathcal{U}_1(\mathcal{L}) = 1; \\
-1, & \text{if } \mathcal{U}_2(\mathcal{L}) = 1; \\
0, & \text{if not}; 
\end{cases}
\]

\[
\mathcal{U}_1(\mathcal{L}) = (B(\mathcal{D}_j, \mathcal{L}) > c_2) \land (B(\mathcal{C}_j, \mathcal{L}) < c_1);
\]

\[
\mathcal{U}_2(\mathcal{L}) = (B(\mathcal{C}_j, \mathcal{L}) > c_2) \land (B(\mathcal{D}_j, \mathcal{L}) < c_1); 
\]

Here, \(B(\mathcal{D}_j, \mathcal{L})\), \(B(\mathcal{C}_j, \mathcal{L})\) are estimates of the image \(\mathcal{L}\) belonging to the sets \(\mathcal{D}_j\) and \(\mathcal{C}_j\), respectively. These estimates are calculated in the same way as those shown in the eleven stages of determining diagnostic algorithms.

If \(R(\mathcal{L}) = 1\), then the object belongs to the subset \(\mathcal{D}_j\), if \(R(\mathcal{L}) = -1\), then object belongs to the subset \(\mathcal{C}_j\), if \(R(\mathcal{L}) = 0\), then it is impossible to determine the identity of the image \(\mathcal{L}\) to a subset.

This problem of determining the diagnosis is: 1) solved on the basis classical recognition algorithm based on the principle of potentials [13]; 2) using proposed algorithm. Table 2 shows the results of the experimental studies conducted to solve the problem under consideration using algorithms based on the principle of potentials.

Table 2. Results of solving a diagnostic problem using a classical algorithm based on the principle of potentials

<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Number of correct diagnoses</th>
<th>Number of false diagnoses</th>
<th>Uncertain diagnosis</th>
<th>Diagnostic accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>(D_1)</td>
<td>34</td>
<td>12</td>
<td>4</td>
<td>68%</td>
</tr>
<tr>
<td>(D_2)</td>
<td>36</td>
<td>11</td>
<td>3</td>
<td>72%</td>
</tr>
</tbody>
</table>

Table 3 shows the results of the experimental studies conducted to solve the problem under consideration using the proposed algorithm.
Table 3. Results of solving the diagnostic problem using the proposed algorithm

<table>
<thead>
<tr>
<th></th>
<th>Diagnosis</th>
<th>Number of correct diagnoses</th>
<th>Number of false diagnoses</th>
<th>Uncertain diagnosis</th>
<th>Diagnostic accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_1$</td>
<td></td>
<td>45</td>
<td>4</td>
<td>1</td>
<td>90%</td>
</tr>
<tr>
<td>$D_2$</td>
<td></td>
<td>42</td>
<td>6</td>
<td>2</td>
<td>84%</td>
</tr>
</tbody>
</table>

According to the results of Table 2, when using the classical algorithm, the phytosanitary status was correctly recognized 70 times out of 100 studied wheat leaves, which is 70%.

When using the proposed algorithm, 87 objects out of 100 (images of leaves) were correctly recognized, which is 87% (Table 3).

A comparison of the results obtained shows that the diagnostic accuracy of the proposed algorithm is higher than that of the other second algorithm. The high diagnostic accuracy of this algorithm is explained by the following:

1) the presented model of diagnostic algorithms takes into account the characteristic features of diagnostic features of wheat leaf images;
2) performing a number of additional procedures to improve diagnostic results.

It should also be noted that the diagnosis under consideration is carried out according to preferred diagnostic criteria.

5 Conclusion

One of the main problems of our time is crop management, based on diagnosing the phytosanitary state of crops and providing information for making decisions on their protection. However, the issues of developing and using automated systems for diagnosing diseases of cultivated plants have not been fully resolved.

A model of algorithms for diagnosing the phytosanitary status of cultivated plants based on leaf images has been developed. The main idea of the proposed model is to recognize the phytosanitary status of agricultural crops based on mutual comparison of diagnostic features.

In this case, the formation of diagnostic features is based on the calculation of various statistical characteristics for each part (fragment) of a given image.

In the process of solving a practical problem, the following became clear: 1) the developed diagnostic model can be used in the development of various software packages aimed at solving problems of classifying objects presented in the form of images; 2) at the stage of forming subsets of “mutually unrelated” features (i.e., determining the number of subsets that need to be separated from the leaf image), the issues of constructing threshold functions in the space of representative diagnostic features turned out to be important. This means the need to continue research taking into account the identified areas.

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