Comparison of algorithm Support Vector Machine and C4.5 for identification of pests and diseases in chili plants

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Abstract. Data from the Central Bureau of Statistics of the population working in the agricultural sector continued to decline from 39.22 million in 2013 to 38.97 million in 2014, the number dropped back to 37.75 million in 2015. According to the MIT G-Lab Team (global entrepreneurship program) concludes five factors that make it difficult to raise agricultural productivity to compete in the domestic market, namely the low education of farmers in dealing with pests, the difficulty of access to finance for rural areas, lack of skills, lack of access to information and lack of application of agricultural technology. Chili plants are plants that are very susceptible to pests so BPS noted a decrease in chili production reaching 25%. Information about chili pests is collected so that it becomes a database that can be used to identify disease pests using the data mining method. The use of data mining algorithms is expected to help in the identification of pests and diseases in chili plants. In this study comparing the performance classification techniques of Support Vector Machine (SVM) and C4.5 algorithms. The attributes used consist of Leaves, Stems, and Fruits. By using each training data and testing data as many as 30 data. The results of the study were conducted, based on the accuracy of SVM, which was 82.33% and C4.5 89.29 %%. The final result of this study was that the accuracy of the C4.5 method was better.

1. Introduction
Information from the Central Statistics Agency (BPS), the number of people working in the agricultural sector continued to decline from 39.22 million in 2013 to 38.97 million in 2014, the number dropped back to 37.75 million in 2015 [1]. According to the MIT Team G-Lab (global entrepreneurship program) concluded five factors that make it difficult to raise agricultural productivity to compete in the domestic market, namely the low education of farmers in overcoming pests, difficulty in access to finance for rural areas, lack of skills, lack of access to information and lack of application of agricultural technology [2].

The factors that influence the income of these farmers are none other than pests and diseases. Pests are a group of plant disrupting organisms that can damage crops both physically and physiologically [3,4]. The lack of information can cause problems for farmers, with alternative information such as systems that can identify pests and diseases, maybe farmers can go out and act faster to deal with pests and the disease. The entry of technology into the world of agriculture is expected to be an alternative for farmers so that farmers can have a lot of information on the world of agriculture which has become
their daily life. The SVM and C4.5 algorithms each have advantages and disadvantages [5]. Therefore, in this study we will make a comparison between the two algorithms to obtain the maximum algorithm in the classification of pests and diseases in chili plants. The comparative parameters of the two algorithms are the level of system accuracy, and algorithm processing time [6].

This article consists of several parts, the first part of the introduction that explains the background of the problem, the two methodologies, the three discussions and the results of the study and the final conclusions of the results of the study.

2. Research methodology

2.1. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a learning machine method that works on the principle of Structural Risk Minimization (SRM) with the aim of finding the best hyperplane that separates two classes in input space [5,7]. The best hyperplane is a hyperplane located in the middle between two sets of objects from two classes. The best separator hyperplane between the two classes can be found by measuring the margin of the hyperplane and looking for the maximum point [8,9]. Margin is the distance between the hyperplane and the closest pattern of each class. The closest pattern is called Support Vector.

Figure 1. SVM concept to search the best hyperplane.

2.2. Algorithm C4.5

The C4.5 algorithm is a well-known algorithm that is used for data classification that has numerical and categorical attributes [6,10]. The results of the classification process in the form of rules can be used to predict the value of the discrete type attribute of the new record [11–14]. C4.5 algorithm itself is a development of the ID3 algorithm, where development is done in terms of, can overcome missing data, can handle continuous data and pruning. In general, the C4.5 algorithm for building decision trees is as follows:

- Select the attribute as root.
- Create a branch for each value.
- Share cases in branches.
- Repeat the process for each branch until all the cases in the branch have the same class [4].

To choose the root attribute, it is based on the highest gain value of the existing attributes. To calculate the gain, use the formula as shown in equation 1 below:

\[
\text{Gain} (S.A) = \text{Entropy} (S) - Z_i = i \text{ Entropy} (S_i)
\]

- \( S \) : set of cases
- \( S_i \) : number of cases on the i-partition
- \( A \) : attribute
- \( | S_r | \) : number of cases in S
3. Discussions

3.1. Data analysis
Following is the implementation of the Support Vector Machine (SVM) and C 4.5 methods in the system of identifying pests and diseases in chili with the case and sample data as follows [5,6,10,15–17]:

| Leaf          | Stem          | Fruit          | Statement   |
|---------------|---------------|----------------|-------------|
| Spotted Yellow| Not Grow      | Not Change     | Plant Disease|
| Spotted Black | Become Small  | Spotted Black  | Plant Disease|
| Become Yellow | Spotted Black | Coloured Yellow| Disease     |
| Become Yellow | Become Small  | Coloured Yellow| Disease     |
| Become Yellow | Spotted Black | Not Change     | Disease     |
| Spotted Black | Not Grow      | Coloured Yellow| Plant Disease|
| Become Yellow | Spotted Black | Not Change     | Disease     |
| Spotted Yellow| Become Small  | Spotted Black  | Plant Disease|
| Become Small  | Spotted Black | Not Change     | Disease     |
| Spotted Yellow| Not Change    | Coloured Yellow| Plant Disease|
| Spotted Black | Become Small  | Not Change     | Plant Disease|
| Become Yellow | Spotted Black | Not Change     | Disease     |
| Spotted Black | Become Small  | Coloured Yellow| Plant Disease|
| Spotted Yellow| Not Grow      | Spotted Black  | Plant Disease|
| Become Yellow | Not Grow      | Coloured Yellow| Disease     |
| Spotted Black | Become Small  | Not Change     | Plant Disease|
| Spotted Yellow| Not Grow      | Coloured Yellow| Plant Disease|
| Become Yellow | Become Small  | Not Change     | Plant Disease|
| Spotted Black | Not Grow      | Coloured Yellow| Plant Disease|

3.2. Calculation of method C 4.5

**Step 1**: Change the data into a model tree:

To determine the initial node, the Gain value is calculated for each attribute using the formula

\[
(S, A) = \text{Entropy}(S) - \sum_{v \in \text{values}(A)} \frac{|S_v|}{|S|} \text{entropy}(S_v)
\]

Previously it was calculated the entropy value of each attribute using the entropy formula

\[
\sum_{i=1}^{c} -p_i \log_2 p_i
\]
Calculate the total entropy of the case first as follows:

\[
Ent\text{ropy } total = - \left( \frac{19}{30} \right) \times \log_2 \left( \frac{19}{30} \right) + - \left( \frac{11}{30} \right) \log_2 \left( \frac{11}{30} \right) = 0.9480
\]

After getting the entropy from the whole case, then analyse each attribute and its values and calculate the gain.

\[
\text{Leaf Gain} = 0.9480 - \left( \frac{10}{30} \right) \times 0 + \left( \frac{9}{30} \right) \times 0.50325 + \left( \frac{11}{30} \right) \times 0.43949 = 1.2602
\]

\[
\text{Gain} = 0.9480 - \left( \frac{11}{30} \right) \times 0.6840 + \left( \frac{11}{30} \right) \times 0.6840 + \left( \frac{8}{30} \right) \times 0.54356 = 0.30149
\]

\[
\text{Fruit Gain} = 0.9480 - \left( \frac{11}{30} \right) \times 0.94566 + \left( \frac{5}{30} \right) \times 0 + \left( \frac{14}{30} \right) \times 0.98522 = 0.14156
\]

From the search for the gain value above, we get a table of gain values in table 2.

| Attribute | Value          | Sum (value) | Sum (Pest) | Sum (Diseases) | Entropy |
|-----------|----------------|-------------|------------|----------------|---------|
| Leaf      | Yellow Spots   | 10          | 10         | 0              | 0       |
|           | Black spots    | 9           | 8          | 1              | 0.50325 |
|           | Yellow         | 11          | 1          | 10             | 0.43949 |
| Stem      | Not growing    | 11          | 9          | 2              | 0.6840  |
|           | Shrinking      | 11          | 9          | 2              | 0.6840  |
|           | Black spots    | 8           | 1          | 7              | 0.5435  |
| Fruit     | Fruitlessness  | 11          | 7          | 4              | 0.9456  |
|           | Black spots    | 5           | 5          | 0              | 0       |
|           | Orange         | 14          | 6          | 8              | 0.9822  |

From the table above, the greatest gain value is obtained, namely the leaf gain value. So that the Leaf is chosen as the initial node.

**Step 2:** Arrange the tree

Arrange the tree starting from the selected node in step 1 as in figure 2:

![Figure 2. First decisions tree.](image-url)
and Fruits. The biggest gain value will be the decision knot under the Leaves of Black Spots and Yellowing. Both steps are carried out repeatedly until the results of the data are obtained.

3.3. Calculation of the SVM method
Support Vector Machine (SVM) is a learning machine method that works on the principle of Structural Risk Minimization (SRM) with the aim of finding the best hyperplane that separates two classes in input space.

Table 3. Criteria and weighting according to samples from plantation.

| Leaf | Stem | Fruit |
|------|------|-------|
| 50%  | 20%  | 30%   |

Operational variables and equations used:

Table 4. Training data samples.

| No | Leaf | Stem | Fruit | Goal |
|----|------|------|-------|------|
| 1  | 2    | 0    | 0     | 1    |
| 2  | 1    | 0    | 0     | 0    |
| 3  | 0    | 1    | 1     | 1    |
| 4  | 0    | 2    | 1     | 1    |
| 5  | 2    | 0    | 0     | 1    |
| 6  | 1    | 0    | 1     | 1    |
| 7  | 1    | 2    | 2     | 1    |
| 8  | 2    | 1    | 1     | 1    |
| 9  | 0    | 0    | 0     | 0    |
| 10 | 1    | 1    | 1     | 1    |

Table 5. Description criteria.

| Name Criteria | Characters                | Number |
|---------------|---------------------------|--------|
| Leaf          | Spotted Yellow            | 2      |
|               | Spotted Black             | 1      |
|               | Become Yellow             | 0      |
| Stem          | Not Grow                  | 2      |
|               | Become Small              | 1      |
|               | Spotted Black             | 0      |
| Fruit         | Not Fruit                 | 2      |
|               | Spotted Black             | 1      |
|               | Yellow                    | 0      |
| Goal          | Plant Disease             | 1      |
|               | Disease                   | 0      |

Recommendations for diseases and pests with three dividing lines Y1, Y2, Y3

![Figure 3. Three separating rows Y1, Y2, Y3.](image-url)
Table 6. Y1 separator.

| Leaf | Stem | Target |
|------|------|--------|
| 2    | 1    | 1      |
| 1    | 0    | 1      |
| 0    | 1    | 1      |
| 0    | 2    | 1      |
| 2    | 0    | 1      |
| 1    | 0    | 1      |
| 1    | 2    | 1      |
| 2    | 1    | 1      |
| 0    | 0    | 1      |
| 1    | 0    | 1      |

data1 = data (1:2);  
target1 = [1;1;1;1;1;1;1;1;1;1];  
y1 = SVM train (data1, target1)

4. Results

Confusion matrix is one method that can be used to measure the performance of a classification method. Basically confusion matrix contains information that compares the results of the classification carried out by the system with the results of the classification that should be.

Table 7. Confusion matrix.

| Prediction class | 1 | 0 |
|------------------|---|---|
| In Fact Class    | TP| FN|
| 0                | FP| TN|

The information for the following table is stated as follows:

- True POSITIVE (TP), which is the number of documents from class 1 correct and classified as class 1.
- True Negative (TN), which is the number of documents from class 0 that are correctly classified as class 0.
- False Positive (FP), which is the number of documents from class 0 that are incorrectly classified as class 1.
- False Negative (FN), which is the number of documents from class 1 that are incorrectly classified as class 0.

Calculations to find accuracy can be formulated by: \( \text{accuracy} = \frac{TP + FN}{TP + FN + FP + TN} \times 100\% \)
Table 8. Comparison of system results and actual results.

| No | SVM        | C4.5      | EXPERT     |
|----|------------|-----------|------------|
| 1  | Plant Disease | Plant Disease | Plant Disease |
| 2  | Plant Disease | Plant Disease | Plant Disease |
| 3  | Disease     | Disease    | Disease    |
| 4  | Disease     | Disease    | Disease    |
| 5  | Disease     | Plant Disease | Plant Disease |
| 6  | Plant Disease | Plant Disease | Plant Disease |
| 7  | Disease     | Disease    | Disease    |
| 8  | Plant Disease | Plant Disease | Plant Disease |
| 9  | Disease     | Disease    | Disease    |
| 10 | Plant Disease | Plant Disease | Plant Disease |
| 11 | Plant Disease | Plant Disease | Plant Disease |
| 12 | Disease     | Disease    | Disease    |
| 13 | Plant Disease | Plant Disease | Plant Disease |
| 14 | Plant Disease | Plant Disease | Plant Disease |
| 15 | Plant Disease | Plant Disease | Plant Disease |
| 16 | Plant Disease | Plant Disease | Plant Disease |
| 17 | Disease     | Plant Disease | Plant Disease |
| 18 | Plant Disease | Plant Disease | Plant Disease |
| 19 | Plant Disease | Plant Disease | Plant Disease |
| 20 | Plant Disease | Plant Disease | Plant Disease |
| 21 | Plant Disease | Plant Disease | Plant Disease |
| 22 | Plant Disease | Plant Disease | Plant Disease |
| 23 | Plant Disease | Plant Disease | Plant Disease |
| 24 | Plant Disease | Plant Disease | Plant Disease |
| 25 | Plant Disease | Plant Disease | Plant Disease |
| 26 | Plant Disease | Plant Disease | Plant Disease |
| 27 | Disease     | Disease    | Disease    |
| 28 | Plant Disease | ----       | Disease    |
| 29 | Disease     | Disease    | Disease    |
| 30 | Disease     | Disease    | Plant Disease |

Based on the comparison table above, the calculation of SVM and C4.5 results is obtained as follows:

4.1. SVM algorithm

Table 9. Confusion matrix SVM.

| EXPERT RESULTS | Plant Disease | Disease |
|----------------|---------------|---------|
| SVM            | 17            | 3       |
| Disease        | 2             | 8       |

The validity of the system is assessed by counting TP, TN, FP, and FN values from Table 9.

\[
\begin{align*}
TP &= 17 + 8 = 25 \\
TN &= 8 + 17 = 25 \\
FP &= 2 + 3 = 5 \\
FN &= 3 + 2 = 5
\end{align*}
\]

\[
System\ performance = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%
\]

\[
System\ performance = \frac{25}{25 + 25 + 5 + 5} \times 100\%
\]
System performance = \frac{50}{60} \times 100% \\
System performance = 83.33% \\

4.2. Algorithm C4.5

Table 10. Confusion matrix C4.5.

| Expert Result | Plant Disease | Disease |
|---------------|---------------|--------|
| C4.5 RESULT   | Plant Disease | 18     | 2      |
|               | Disease       | 1      | 7      |

The validity of the system is assessed by counting TP, TN, FP, and FN values from Table 10.

TP = 18 + 7 = 25 \\
TN = 8 + 17 = 25 \\
FP = 1 + 2 = 3 \\
FN = 2 + 1 = 3 \\
System performance = \frac{TP + TN}{25 + 25} \times 100% \\
System performance = \frac{50}{56} \times 100% \\
System performance = 89.29% \\

5. Conclusion

The results of a comparative study of Support Vector machine and C4.5 algorithms in Identifying Pests and Diseases in Chili Plants (Case Study of Cintarasa Village Plantation) can be seen that C4.5 algorithm is more accurate than SVM algorithm with C4.5 89.29% accuracy while SVM Algorithm 82.33 %. In SVM algorithm speed is faster than c4.5 algorithm because SVM data processing is simpler than C4.5.

As the end of the research, the researcher presented several suggestions that were expected to be useful for the interests of the parties concerned. These suggestions are other researchers, namely the discussion in this study is limited to only two algorithms namely SVM and C4.5, it is expected that the next researcher can examine other algorithms or other datasets.

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