Diagnostics of plant diseases based on symptoms from leaf images

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Abstract. The paper develops algorithms for diagnosing plant diseases based on symptoms from leaf images. Various features, such as changes in color, shape, and texture of leaves, associated with diseases are analyzed. It investigates how symptoms affect the accuracy of disease recognition using machine learning. It is revealed that the use of visual symptoms and other symptoms significantly improves diagnostic results. Not only that but it is determined that the combination of deep learning and classical image processing methods allows for high accuracy in disease detection. Furthermore, it is established that the developed algorithms can identify plant diseases based on symptoms detected in leaf images. The results of testing the algorithms on real data show their applicability in the real world.

1 Introduction

Plant diseases threaten agricultural production and can cause significant crop losses. Increasing agricultural productivity and sustainability depends on the timely detection and treatment of diseases. Traditional diagnostic methods such as visual inspection and laboratory testing are time-consuming and labor-intensive, making them ineffective over large areas and with high infection rates. The introduction of machine learning and computer vision has made it possible to automate the process of plant disease diagnosis. Modern image processing algorithms can analyze leaf images and determine the presence and type of disease based on changes in color, shape, and texture. These approaches reduce diagnosis time and improve the accuracy of disease recognition at early stages. This paper discusses the development of algorithms that can identify plant diseases using leaf images, given the symptoms that can be seen in these images. It focuses on exploring different approaches to image processing and machine learning and how they can be used to recognize plant diseases. The study [1] uses three optimization strategies to identify plant leaf diseases. The preprocessing step of the proposed methodology involves removing the noise signals from the input image using the modified Wiener filter (MWF). In the study

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[2], the objectives of designing and building an intelligent leaf disease classification mechanism are achieved using artificial intelligence and computer vision techniques. To evaluate the performance, two methodologies are considered and their modeling results are compared. Many feature extraction methods have been used individually and they failed to detect two or more plant diseases during the feature extraction and classification process. The study [3] considers the use of hybrid machine-learning methods for plant disease detection and classification. The plant image data samples were obtained from the open-source Plant Village image dataset where the images were preprocessed in grayscale with RGB color. The data preprocessing was done using the K-means clustering method. The features were extracted using histogram-oriented gradient and local binary pattern. Principal component analysis was used as a feature selection method. The study [4] considers various bacterial and fungal diseases of pepper and the methods for identifying and classifying these diseases using image processing techniques. Bacteria, fungi, and viruses can infect peppers, and disease symptoms can be detected by looking at the stems, leaves, or fruits of peppers. A new computer algorithm is proposed to differentiate plant disease symptoms and features from symptoms not expressed in plant leaf tissues [5]. The simplest algorithm manipulates the histograms of the HSV (H) and L*a*b* color channels. In the algorithmic process, each step is performed automatically except for the last step, in which the user selects the channel (H or a) that provides the best differentiation.

The classification of citrus leaf diseases is presented in [6]. First, the problems related to the detection and classification accuracy are considered. Using the images of infected leaves, crop diseases can be predicted [7]. The proposed hybrid model is used to find bacterial spot on peach plants based on leaf photographs, but it can also be used to find any plant diseases. Manual identification is a time-consuming process that requires a prior understanding of the plant such as its shape, odor, and texture. Therefore, the study [9] aims to introduce a computerized species recognition method to identify early grass disease by referring to these characteristics. A novel method for identifying plant leaf diseases is presented in [10]. Image segmentation and image classification are the main components of the method. The paper [11] discusses the advantages and disadvantages of these studies to highlight the important aspects of the study. The most common infections and study scenarios that are conducted at different stages of the disease detection system are presented.

In the study [15], six color and twenty-two texture features were evaluated. One-to-one classification of plant diseases is performed using support vector machines. The proposed disease identification model has a standard deviation of 0.57 under ten-fold cross-validation and achieves an accuracy of 98.79%. The accuracy on the self-collected dataset is 82.47% for disease identification and 91.40% for healthy/sick classification. The reported performance metrics are the highest among feature-based methods and are better or comparable to existing approaches. This makes the method most suitable for automated leaf-based plant disease identification. It is possible to extend this prototype system by adding more disease categories or targeting specific crops or disease categories. Traditional set theory and classical logic methods may not be effective in solving complex problems in the modern world, where information is often incomplete, uncertain, or contradictory. Advanced set theories such as neutrosophic sets, intuitionistic fuzzy sets and fuzzy sets are crucial in such settings. The idea of bipolar neutrosophic sets is one of the latest advances in this field. It was proposed to represent and handle data more accurately and flexibly under uncertainty and contradictions.

2 Methods

The neutrosophic set contains three parameters: the degree of true membership, the degree of uncertainty of membership, and the degree of falsehood of membership.

If X of the set contains x. Then the neutrosophic set $NS(A)$ is defined by the formula:

$$NS(A)=\{\langle x,T_A(x),I_A(x),F_A(x)\rangle : x\in X\} \tag{1}$$

Where $T_A(x),I_A(x),F_A(x)$ is the degree of belonging to the truth, the degree of belonging to uncertainty and the degree of belonging to falsity similarly. In this situation $T_A(x),I_A(x),F_A(x):X\to\left]^-0,1^+\right[$ in addition to the following condition $^-0\le T_A(x)+I_A(x)+F_A(x)\le 3^+$. [1-3].

A single-valued neutrosophic set (SVNS) is a direct result of a neutrosophic set if it is defined on the standard unit interval [0, 1] instead of the non-standard unit interval $\left]^-0,1^+\right[$. A single-valued neutrosophic set SVNS(A) is defined by:

$$SVNS(A)=\{\langle x,T_A(x),I_A(x),F_A(x)\rangle : x\in X\} \tag{2}$$

Where $T_A(x),I_A(x),F_A(x):X\to[0,1]$ such that $^-0\le T_A(x)+I_A(x)+F_A(x)\le 3^+$. [4,5,6]

Let X be a universal set that contains arbitrary points x. A bipolar neutrosophic set (BNS) is defined:

$$BNS(A)=\{\langle x,T_A^+(x),I_A^+(x),F_A^+(x),x,T_A^-(x),I_A^-(x),F_A^-\rangle : x\in X\} \tag{3}$$

Where $T_A^+,I_A^+,F_A^+:\mathrm{E}\to[0,1]$ (positive degrees of membership), $T_A^-,I_A^-,F_A^-:\mathrm{E}\to[-0,1]$(Negative degrees of membership), such that:

$$0\le T_A^+(x),I_A^+(x),F_A^+(x)\le 3,-3\le T_A^-(x),I_A^-(x),F_A^-(x)\le 0. \tag{4}$$

Where $0\le T_A^+(x)+I_A^+(x)+F_A^+(x)\le 3$ and $^-3\le T_A^-(x)+I_A^-(x)+F_A^-(x)\le 0$. Also $T_A^+(x),I_A^+(x),F_A^+(x)\to[0,1]$ and $T_A^-(x),I_A^-(x),F_A^-(x)\to[-0,1]$.

Grayscale image in the bipolar neutrosophic set. Image in the neutrosophic set.

A pixel P of an image is stated as $P(T,I,F)$ and belongs to W in the following way: it makes t% true, i% uncertain, and f% false in the set of bright pixels, where t transforms into T , i transforms into I, and f transforms into F. Each element has a value in $[0,1]$.

The pixel $P(i,j)$ in the image sphere is transformed into a neutrosophic multiple image, $P_{NS}(i,j)=T(i,j),I(i,j),F(i,j)$ where $T(i,j),I(i,j),F(i,j)$ demonstrate the

probabilities belonging to the white set, the indefinite set and the non-white set respectively, which are defined as:

$$T(i,j)=\frac{\bar{g}(i,j)-\overline{g_{\min}}}{\overline{g_{\max}}-\overline{g_{\min}}};I(i,j)=\frac{\delta(i,j)-\delta_{\min}}{\delta_{\max}-\delta_{\min}};F(i,j)=1-T(i,j)=\frac{\overline{g_{\max}}-\bar{g}(i,j)}{\overline{g_{\max}}-\overline{g_{\min}}} \tag{5}$$

Where $\bar{g}(i,j)$ represents the average pixel intensity in some neighborhood in W. Here,

$$\begin{gathered}\bar{g}(i,j)=\frac{1}{W\times W}\sum_{m=i-w/2}^{i+w/2}\sum_{n=j-w/2}^{j+w/2}g(m,n),\\ \delta(i,j)=\left|g(i,j)-\bar{g}(i,j)\right|,\delta_{max}=\max\delta(i,j)\quad\delta_{\min}=\min\delta(i,j),\\ \delta_{\max}=\max\delta(i,j);\delta_{\min}=\min\delta(i,j).\end{gathered} \tag{7}$$

Fig. 1. Original image

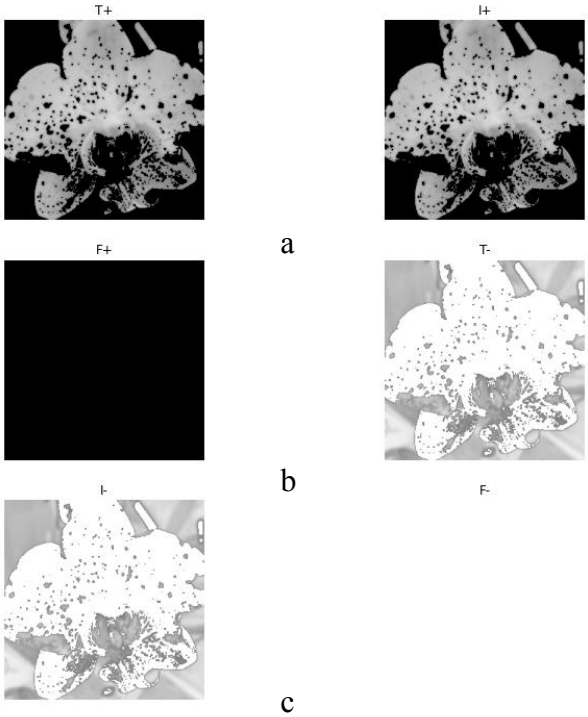

Fig. 2. Neutrosophic multiple images after contrast enhancement (a) T-sets (b) I-sets (c) F-sets.

The original image had a set of truth, uncertainty and false membership, which are represented by the above images. For image analysis, we mainly refer to the truth membership domain and uncertainty domain, where the truth membership set is related to the uncertainty set.

3 Results

In the task of determining the phytosanitary condition of crop plants, photographs of leaves provide useful information. The problem of monitoring and diagnosing plant diseases in agriculture can be solved using digital images, image processing, pattern recognition, and automatic classification tools. For example, digital photographs can be processed to highlight leaf characteristics and other features that may indicate the presence of a disease. These images can then be automatically analyzed and classified using image processing and pattern recognition techniques. Machine learning algorithms trained on labeled data consisting of images of plants with a known phytosanitary condition can help in this. In this way, the system can automatically detect features of diseases and, based on these features, judge the condition of the plants. Autonomous augmentation was used to reconstruct the dataset from the original dataset. This dataset consists of approximately 87,000 RGB images of healthy and diseased crop leaves, divided into 46 classes. The overall dataset is divided into training and validation sets in an 80/20 ratio while maintaining the catalog structure. Later, a new catalog with 33 test images is created for prediction.

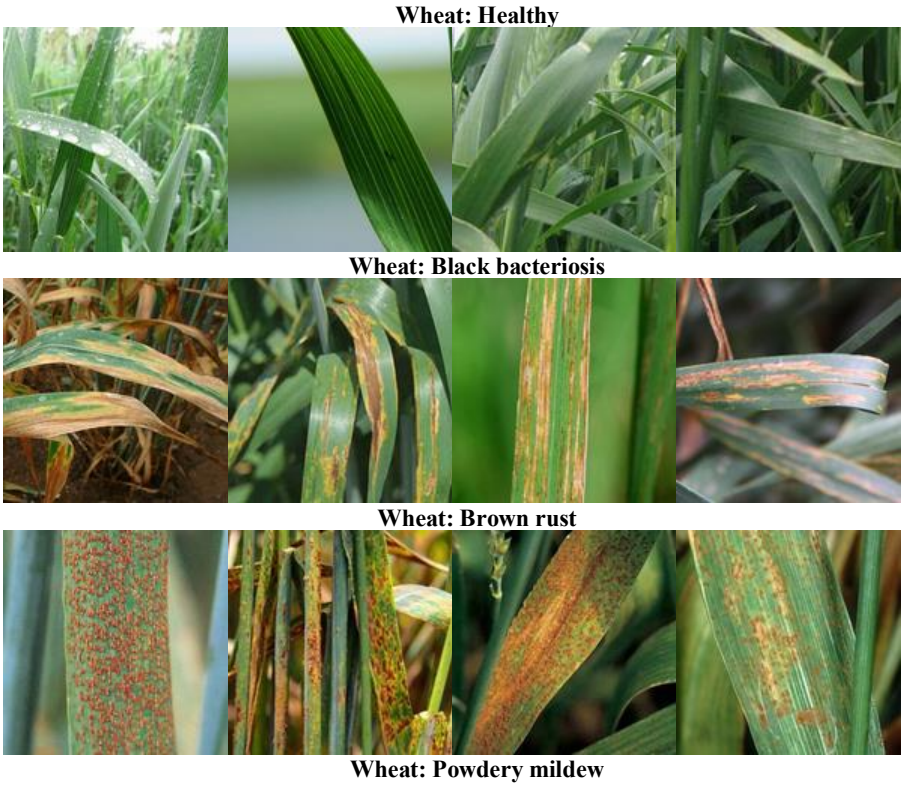

Fig. 3. Examples of images of healthy and diseased plant leaves.

A graphical dependence showing the average value of accuracy and distribution error for the number of training epochs was constructed based on the obtained data (Figures 4-5).

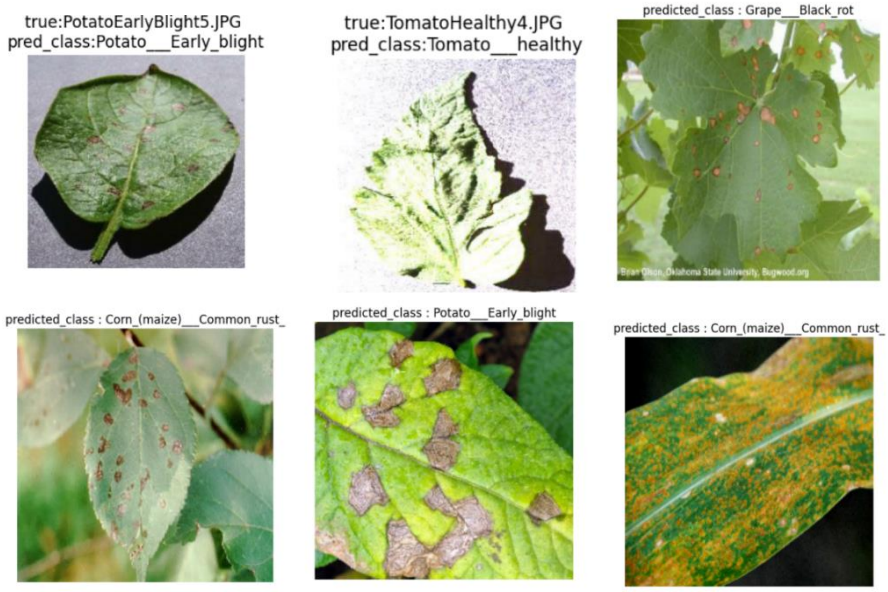

Fig. 4. Examples of the results obtained.

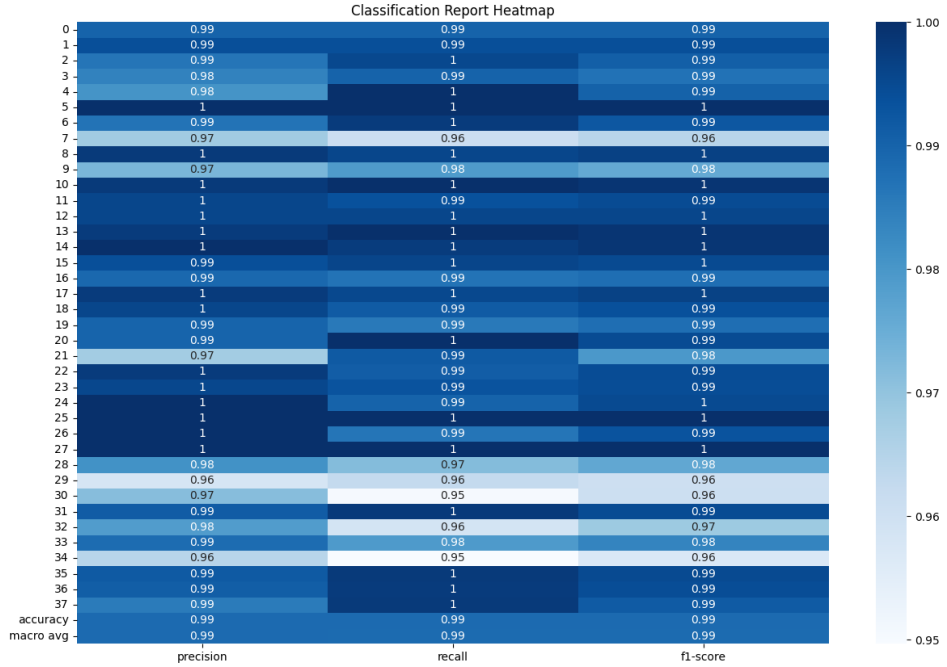

Fig. 5. Classification Report Heatmap.

Instant identification while scanning a field eliminates the need to spend time searching for problems and recording the results. In addition, the recorded photos can be viewed by others and used as a reference for subsequent actions. Growers use the tool as an assistant or as a way to get a second opinion when in doubt because they find it difficult to make an accurate diagnosis. This is especially important in situations where other sources of advice

are not available; this can be especially important in countries where the ratio between agronomists and growers is very high. Visual inspection is critical to plant health. Growers make decisions based on the symptoms that can be seen on plants because lab tests are not a practical tool for daily diagnosis due to expense and turnaround time. Plant inspection is time-consuming and often leaves growers uncertain. Crop consultants are available to help growers make decisions and minimize errors. However, what to do if such help is not available? Fortunately, modern technology can help. A huge increase in the productivity of the artificial intelligence research community has made it possible to use AI to identify plant diseases. From the above, we can conclude that the CNN convolutional neural network experimented at a high level. For further training of the neural network, it is also necessary to create an extensive database of plant diseases.

4 Conclusion

The study examined features indicating the presence of diseases, such as changes in color, shape, and texture of leaves. The combination of visual symptoms and machine learning showed a significant improvement in the accuracy of disease recognition compared to using separate methods. The study confirmed that image pre-processing, which includes segmentation and color correction, can improve classification results. The algorithms created in the study demonstrated high efficiency in identifying various plant diseases. Even at the early stages of the disease, deep neural networks provide high recognition accuracy, which makes it possible to automate the process of analyzing visual data. The program developed based on the proposed algorithms was successfully tested on real data, which confirms its applicability in real agriculture. The result of the work is that the recommended methods can be integrated into crop monitoring systems. This will allow farmers to minimize crop losses and promptly respond to diseases. Automation of the image-based diagnostic process not only saves time and resources but also increases the overall accuracy of disease detection, reducing the influence of the human factor and errors associated with visual assessment of plant condition. Further research into improving diagnostic methods based on computer vision and machine learning is emphasized. Future development of these technologies will allow for the creation of even more accurate and adaptive systems that can not only recognize diseases but also offer solutions to eliminate them using the analysis of external factors and symptoms. In addition to opening up new opportunities for automating plant disease monitoring and diagnostic processes, these studies make a significant contribution to the development of intelligent systems in agriculture. Ultimately, this will lead to increased productivity and sustainability of agro-industrial complexes.

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