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Early discovery and classification of plant diseases with convolutional neural networks and nano biosensors

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Abstract

Objective

Infections caused by viruses and bacteria are the primary microbe-related problems that significantly decrease agricultural productivity worldwide. Currently, the identification of pathogens is particularly difficult due to the prevailing living conditions. Biosensors are now widely used for the surveillance of microbial and viral particles.

Materials and Methods

Preventing crop loss and reducing economic and environmental effects requires early plant disease identification. Tracking plant infection nanoparticles has made early disease diagnosis possible due to nanotechnology and biosensors. Pathogens including bacteria, fungi, and viruses form nanoparticles with unique chemical traces that may be detected by sensitive nano biosensors. Precision agriculture now allows faster responses and more specific disease control. Deep Learning (DL) methods, particularly Convolutional Neural Networks (CNNs), can learn hierarchical patterns in nano biosensor data and accurately distinguish healthy and infected plants, even in early infection stages. This expands precision agriculture and disease management.

Results

The study utilizes the ECPD-CNN-NBS model to identify Bacterial Spot (BS) disease in peach plants by analyzing their leaf images. The model can also be employed for ECPD detection. The experiments conducted in this paper utilize the publicly accessible PlantVillage dataset to obtain leaf pictures of peach plants.

Conclusions

The proposed system attains a learning accuracy of 99.55% and a testing accuracy of 99.01% by utilizing 10,013 learning parameters.

Keywords: Bacterial spot, convolutional neural networks, nano biosensors, plant diseases, PlantVillage dataset

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Introduction

As the world's population grows, there is pressure on agriculture to increase production and ensure enough food for everyone. Food security worldwide is affected by crop productivity in a big way (Radhika & Masood 2022). Losses in production caused by climate change may occur in two ways: directly or indirectly. One way is through the propagation and impact of Plant Pathogens (PP). The organism that spreads the disease to plants is called PP. Some PP relatives make plants or animals sick, but most PP is bad for plants (Srinivasa et al. 2023). These germs are known as "trans-kingdom" pathogens. Unlike people, plants usually take a long time to get better after getting sick. Plant pathologists work to stop diseases from happening in the first place and cut down on their symptoms and spread. Plant diseases (PD) hurt the economy by making it harder for organisms to make food, fiber, and biofuels. PD can happen to any plant, even citrus, grains, ornamental shrubs, and trees in forests. For instance, Mitra (2021) says that PD costs the world economy more than $220 billion. So, finding and diagnosing PP as soon as possible is significant for better, less expensive rehabilitation. To deal with the growth of PP and keep its effects on community farms and the economy to a minimum, we need to plan and use scientific methods.

PD can be controlled in several ways, including using clean seeds, rotating crops, choosing resistant varieties, treating leaves with fungicides, and other farming and chemical methods (Lamichhane et al. 2020). To stop PD, fungicides are employed. Long-term (or extensive) application of fungicides, on the other hand, has made some fungal populations less sensitive to different activity systems (Ons et al. 2020). So, it's important to come up with ways to quickly, accurately, and precisely find the pathogens that cause disease so that the right chemicals can be used in a preventative way (Surendar et al. 2024). Since there will be less need for chemical treatments in the farming system, there will be fewer dominant traits and possible bad effects on the pathogen population in the atmosphere further down the line. ECPD is important for monitoring plant health and using an effective Informed Disease Management (IDM) method. It is important to tell the difference between the groups that trigger PD because distinct fungal pathogens change plants similarly during PD. For plants that are easily hurt, the most obvious signs are often changes in shape and color, especially necrotic patches, and sometimes the loss of the plant's root system or leaves. To have informed management, you must also know about infections, even if they don't show symptoms (Kuska et al. 2022). A skilled grower or pathologist is needed to inspect crops visually. This is the oldest and most reliable way to diagnose diseases and possibly pathogens. By the time a visual detection is made, the infection will have spread to host populations. Much attention has been paid to developing ECPD techniques that can identify pathogens more quickly, accurately, and sensitively.

There are two main ways to identify PD, according to an interesting new review (Lee et al. 2020), which are direct. Some examples of direct approaches are molecular approaches like Polymerase Chain Reaction (PCR) and its variants like Reverse Transcription (RT)-PCR, and serological techniques like Enzyme-Linked Immuno Sorbent Assay (ELISA) (Tayebeh et al., 2017) and flow cytometry. Image-based phenotyping techniques (IPT) have taken the place of visual detection as a way to find Parkinson's disease because they are non-destructive and portable, and images and software are used to analyze larger samples. Some of these methods are hyperspectral imaging, fluorescent chlorophyll, and visibility in light. It's also necessary to be able to interpret datasets using computational methods and theories (Yang et al. 2021). This imaging method allows for gathering data that the human eye can't see. The new method in (Iqbal et al. 2018) was used to create the DL approach, which automatically sorts and classifies based on images of their leaves. The model could tell the difference between healthy leaves and 13 different types of diseases (Ferentinos 2018). Risk-based controls involve taking host plants out of a certain area after they are found to be infected, focusing on infections that don't show any symptoms using epidemiology based on past information to understand how models can be used in different places, and using management methods that change over time (Dessy et al. 2023). To these conventional and novel methods, newer ones (Kumar & Arora 2020), like biosensors that use nano- and bio-molecular structures to focus problems more than old-fashioned ways of diagnosing, have been added. Using nanomaterials and transmission procedures that work well for various biomolecules (Oliveira et al. 2014) to create the required method for attaining the intended performance levels is feasible and has a lot of flexibility. The biosensors are now an important part of ECPD.

Nanotechnology has helped solve many problems in agriculture, such as finding and controlling PD (Fu et al. 2020). Nanoparticles have interesting electronic and optical properties and are used with many different materials in electronics and sensing. Nanomaterials are used in sensor design because they are good for collecting bio-recognition parts in an eco-friendly way, and they have a lot of surface area, good microelectronic conductivity, and plasmonic properties that make detection better. Nano-based materials are mixed with fungicides and insecticides in smaller amounts. The food and agriculture industries can quickly manage several PDs using portable diagnostic tools, Nano-sensors, and NBS to identify areas in ECPD (Xu et al. 2023). This paper looks at how Machine Learning (ML) and DL can be used to analyze sensing data. DL can help biosensors solve problems in new ways, and it could also turn simple biosensors into smart ones that can guess the amount of analyte or species present using a Decision-Making System (DMS) (Rahmani et al. 2023). Many NBS might react with pathogens or compounds that aren't meant to be there because their biochemical properties are similar. For precise and trustworthy PD detection, it is important to deal with the problem of sensor specificity and reduce cross-reactivity as much as possible (Negi & Anand 2024) One important gap is the lack of effective data analysis tools that can take NBS's data into useful information for farmers (Zoran et al. 2022). These sensors can be more useful if connected to data analysis and DMS. By combining accurate pathogen analysis with effective signaling mechanisms, these NBS provide a strong foundation for quick, sensitive, and accurate PD in various settings, from farming and healthcare to ecological monitoring. Moreover, data generation in agriculture and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Mohammadabadi et al. 2024). These data are obtained from studying products, foods, diseases, and biological molecules, such as metabolites, proteins, RNA, and DNA, to understand the role of these products and molecules in determining the structure, function, and dynamics of living

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systems (Pour Hamidi et al. 2017). Functional genomics is a field of research that aims to characterize the function and interaction of all the major components (DNA, RNA, proteins, and metabolites, along with their modifications) that contribute to the set of observable characteristics of a cell or individual (i.e., phenotype). Artificial neural networks have been proposed to alleviate this limitation of traditional regression methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy (Pour Hamidi et al. 2017). Agricultural data can be too large and complex to handle through visual analysis or statistical correlations. This has encouraged the use of machine intelligence or artificial intelligence (Ghotbaldini et al. 2019). Thus, this review aimed to AI in agricultural applications.

Materials and Methods

Early discovery and classification of plant diseases with convolutional neural networks and nano biosensors (ECPD-CNN-NBS): The ECPD technique enhances the efficacy of NBS applications in agricultural cultivation and analysis of PD management. This enhances productivity by providing precise suggestions derived from sequential and distinct input data streams from NBS. The agricultural fields must provide data streams, specifically regarding the detection of plant diseases at various time intervals. This method aims to minimize the error in the analysis of ECPD by focusing on discrete information. The task involves identifying instances of discrete data that differ from previous iterations regarding sequencing and likelihood. The NBS-based ECPD scenario utilizes convolutional neural networks (CNN) classification to collect specific information such as the height of plants, wellness, moisture, temperature, etc (Camgözlü & Kutlu 2023). The plant observation patterns are stored as reports from the prior iterated instances. Figure 1 illustrates the suggested ECPD-CNN-NBS methodology being utilized in an agricultural context.

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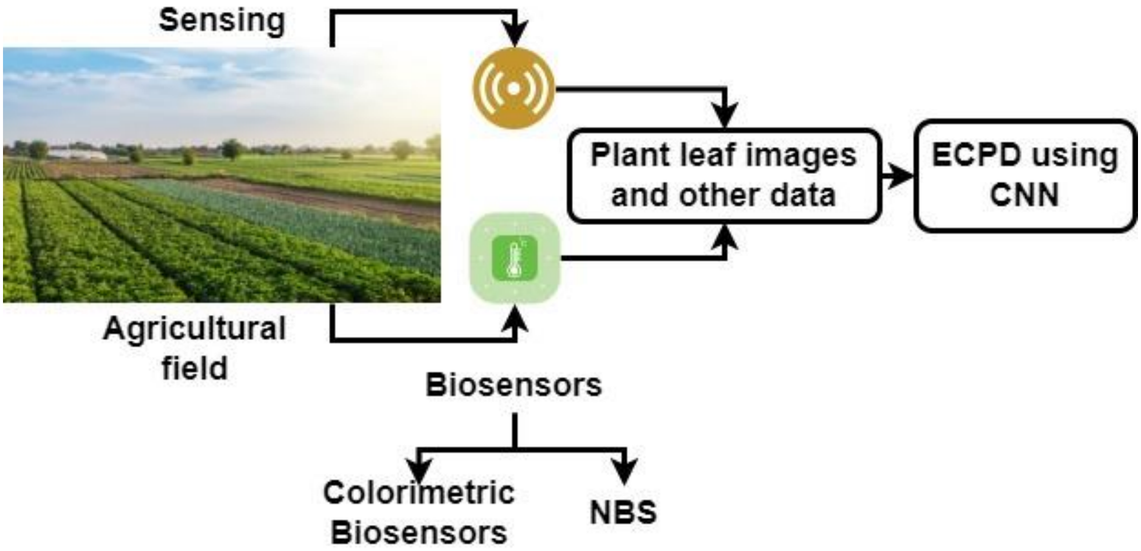

Figure 1. Framework of ECPD-CNN-NBS

The proposed ECPD method uses biosensors to monitor the activities and modifications of the plants and agricultural areas. Conventional pathogen detection methods are time-consuming and expensive for rural farmers. Identifying the causal agent of PD is crucial in effectively managing the disease in the growing environment. Detecting infections during the cell culture phase can prevent substantial crop damage as numerous pathogenic microorganisms, such as viruses and bacteria, are transferred from seeds to plants. PD detection is used in fast-response scenarios in nurseries, natural settings, and in the micropropagation stage of crop production to identify microscopic organisms, such as bacteria, viruses, and fungi, in damaged plant tissue. The NBS-based ECPD model utilizes CNN classification to gather specific information, including plant height, wellness, moisture, temperature, and other relevant factors.

This research demonstrates the utilization of various types of NBS based on electrophysiological signals, colorimeters, nanotechnology, and luminescence to develop new and highly sensitive biosensing systems to detect and identify PDs. The visual confirmation of the presence of harmful microbes in a specimen can be achieved by detecting changes in color using a colorimetric NBS, which makes this optical biosensor attractive. Optical biosensors can detect and measure the emission or absorption of light resulting from a biological, physical, or chemical process. However, Electrochemical NBS can generate current, voltage, or impedimetric measurements by utilizing biological reactions that induce electron transfer between a modified electrode and an analyte in a liquid solution. Another approach involves using nanotechnology, which may have a more organic nature, to address various agricultural challenges, including identifying and controlling PDs.

A wide range of substances, including nanoparticles, can be utilized due to their fascinating electrical and optical properties, making them suitable for applications in electronics and sensing. Nanoparticles possess a large surface area, strong electrical conductivity, and plasmonic characteristics that amplify the detection limitations. This may elucidate the widespread use of nanomaterials in the development of sensors. Using signal enhancement techniques may potentially jeopardize the effectiveness of conventional methods to enhance targets. Applying nano-based kits, NBS, and other mobile diagnostic technologies can greatly assist the food and agricultural sectors in efficiently detecting and managing different PDs. The detection and classification are determined by the sequence and difference in the analysis of gathered data from agricultural fields. The NBS-based ECPD is furnished with sensing units to gather data on various parameters, including the identification of diseases, temperature, drought, humidity, height, crop output analysis, wellness, soil erosion, etc. This information is used to process distinct characteristics of the agricultural fields accurately.

The proposed ECPD incorporates robust and independent information evaluation and disease control based on the definite requirements of the NBS applications. The peach plant is monitored to detect the presence of diseases. The study focuses on various characteristics of the peach plant, including its varieties, structures, weight, color, geometric properties, and refractions. Cloud cover, shades, and time of day significantly impact the color of light entering the sensor when outdoors. Therefore, it is necessary to take frequent white balance measurements to ensure precise calibration. This process typically involves capturing an image using the camera under minimal lighting conditions and utilizing the resulting low-level noise data to calibrate subsequent measurements.

As demonstrated in the preceding section, crop production, and plant monitoring data are collected using NBS positioned over the agricultural field. The collected data is categorized as continuous and discontinuous. Continuous observation involves monitoring a plant's variables, such as moisture, temperature, and height, which remain consistent over time and throughout the day. However, in the context of monitoring distinct information, the instances are not monitored simultaneously or on successive days. The presence of series, difference, and likelihood features increases the probability of errors in accurately processing distinct features, thus reducing reliability. The errors are perceived as a manifestation of disease diagnosis. The proposed technique specifically targets these errors by employing ECPD using CNN.

Convolutional Neural Networks (CNN): Once the input plant images were resized, a CNN was employed to determine whether the images depicted a diseased or healthy plant. Figure 2 illustrates the architecture of a CNN designed specifically for the ECPD using images of peach leaves. The network commences with a series of convolutional layers, followed by a max pooling layer after each one. These layers extract significant characteristics from the input images and decrease their dimensions. The convolutional layers employ three distinct quantities of filters (6, 16, and 16) with a kernel size 3x3. This aids in the detection of boundaries, surface characteristics, and arrangements that are associated with both healthy and diseased plant tissues. The max-pooling layers with a size of 2x2 decrease the spatial dimensions. This enhances the computational efficiency of the model while retaining crucial information.

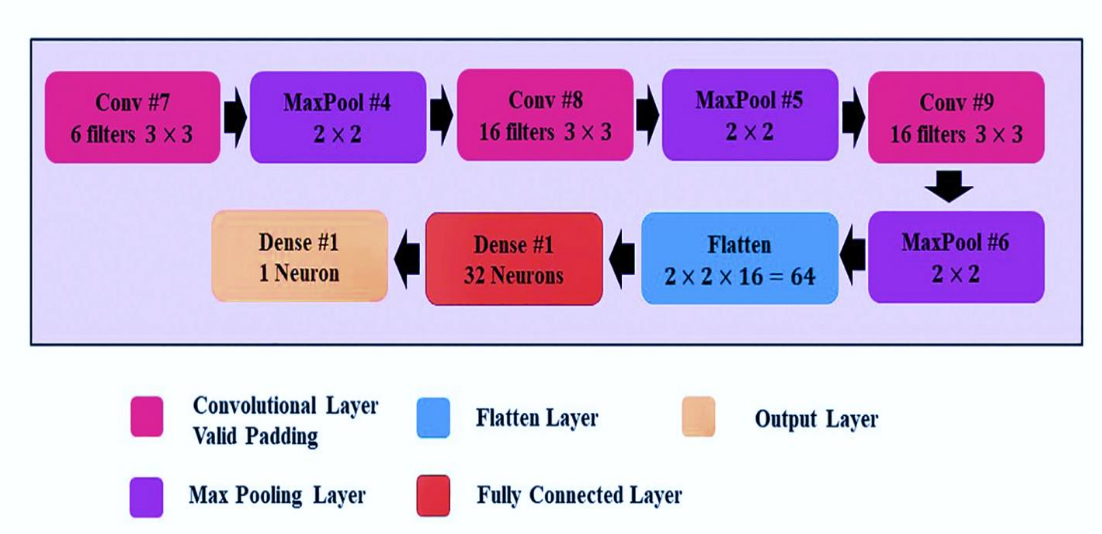

Figure 2. Architecture of CNN for ECPD

Subsequently, the network progresses to fully connected (dense) layers. One layer consists of 32 neurons, while the other contains only one. This represents the result of a binary classification task, most likely distinguishing between a healthy state and a diseased state. The flattening layer transforms the 2D matrix of the final pooling layer into a 1D vector, enabling its utilization for classification purposes. The architecture is designed to efficiently and precisely capture the intricate features of images of peach leaves, enabling the model to distinguish between healthy and diseased conditions. This configuration demonstrates the ability of CNN to autonomously acquire hierarchical features from images, a crucial aspect for the rapid and precise diagnosis of diseases.

Results and discussion

The experiments conducted in this research utilize the Jupyter Notebook designed for the Python programming language. Additionally, alternative programming languages, like Matlab, R, etc., can execute the suggested ECPD model utilizing NBS and CNN. The Keras Application Programming Interface (API) was utilized to construct and train the model. The experiments in

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this paper employ the publicly available Plant Village dataset (plant disease) to acquire images of peach leaves.

Figure 3 illustrates the learning and testing accuracy (%) for 20 epochs using ECPD-CNN-NBS. At first, training and testing accuracy improves quickly, with testing accuracy slightly ahead. By the third epoch, the accuracies of both models reach a stable level of approximately 93%, suggesting that the model is effectively acquiring knowledge. The model's accuracy steadily increases during training, reaching the highest value of 99.55% for training and approximately 99.01% for testing by the 19th epoch. The consistent correlation between training accuracy and testing throughout the epochs indicates that the model effectively applies its knowledge to new data, with minimal indications of overfitting. This demonstrates the model's strength in accurately classifying and detecting PD using CNN and NBS.

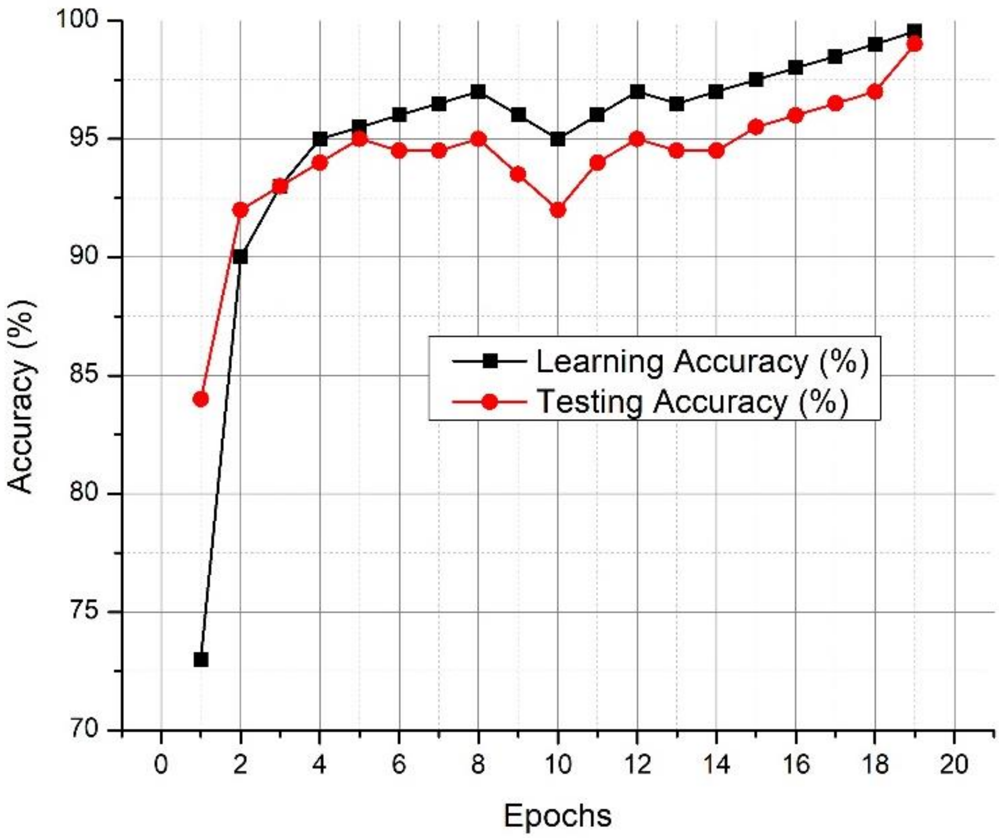

Figure 3. Learning and testing accuracy (%) for varying epochs using ECPD-CNN-NBS

Conclusions: This paper presents a technique called Early Discovery and Classification of Plant Diseases with Convolutional Neural Networks and Nano Biosensors (ECPD-CNN-NBS). ECPD is a prominent NBS application specifically developed to efficiently address seasonal and cultural irregularities that may adversely affect crop farming. The study employs the ECPD-CNN-NBS model to detect the occurrence of Bacterial Spot (BS) disease in peach plants by analyzing their leaf images. In addition, the model can also be used for ECPD detection. The experiments in this paper employ the publicly available PlantVillage dataset to acquire images of peach plant leaves. The proposed system achieves a learning accuracy of 99.55% and a testing accuracy of 99.01% by utilizing 10,013 learning parameters. The utilization of fewer training parameters in the ECPD-CNN-NBS model resulted in a substantial reduction in both the training time for the automatic detection of PD and the time required to identify diseases in plants using the trained model.

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کشف اولیه و طبقه بندی بیماری‌های گیاهی با شبکه‌های عصبی کانولوشنال و نانو حسگرهای زیستی

اف راهمان

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چکیده

هدف: عفونت‌های ناشی از ویروس‌ها و باکتری‌ها، مشکلات اولیه مرتبط با میکروب هستند که به‌طور قابل‌توجهی بهره‌وری کشاورزی را در سراسر جهان کاهش می‌دهند. در حال حاضر، شناسایی عوامل بیماری زا به دلیل شرایط زندگی غالب دشوار است. حسگرهای زیستی امروزه به طور گسترده برای نظارت بر ذرات میکروبی و ویروسی استفاده می شوند.

مواد و روش‌ها: جلوگیری از هدررفت محصول و کاهش اثرات اقتصادی و زیست محیطی نیازمند شناسایی زودهنگام بیماری های گیاهی است. ردیابی نانوذرات آلودگی گیاهی، تشخیص زودهنگام بیماری را به دلیل نانوتکنولوژی و حسگرهای زیستی ممکن کرده است. پاتوژن‌ها از جمله باکتری‌ها، قارچها و ویروس‌ها نانوذراتی را با آثار شیمیایی منحصربه‌فرد تشکیل می‌دهند که ممکن است توسط نانو حسگرهای زیستی حساس شناسایی شوند. کشاورزی دقیق اکنون پاسخ های سریع تر و کنترل بیماری های خاص تر را امکان پذیر می‌کند. روش‌های یادگیری عمیق (DL)، به‌ویژه شبکه‌های عصبی کانولوشن (CNN)، می‌توانند الگوهای سلسله مراتبی را در داده‌های نانو حسگر زیستی بیاموزند و گیاهان سالم و آلوده را به‌طور دقیق تشخیص دهند، حتی در مراحل اولیه آلودگی. این امر کشاورزی دقیق و مدیریت بیماری را گسترش می‌دهد.

نتایج: این مطالعه از مدل ECPD-CNN-NBS برای شناسایی بیماری لکه‌های باکتریایی (BS) در گیاهان هلو با تجزیه و تحلیل تصاویر برگ آنها استفاده می‌کند. این مدل همچنین می‌تواند برای تشخیص ECPD استفاده شود. آزمایش‌های انجام‌شده در این مقاله از مجموعه داده‌های قابل دسترسی عمومی PlantVillage برای به دست آوردن تصاویر برگ گیاهان هلو استفاده می‌کنند.

نتیجه‌گیری: سیستم پیشنهادی با استفاده از ۱۰۰۱۳ پارامتر یادگیری به دقت یادگیری ۹۹.۵۵ درصد و دقت تست ۹۹.۰۱ درصد می‌رسد.

واژه‌های کلیدی: اسپات باکتریایی، بیماری‌های گیاهی، شبکه های عصبی کانولوشنال، مجموعه داده PlantVillage، نانو حسگرهای زیستی

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