Received: 12 August 2023 | Revised: 20 May 2024 | Accepted: 11 August 2024 | Published online: 19 August 2024

RESEARCH ARTICLE

Journal of Data Science and Intelligent Systems
2025, Vol. 3(3) 192–199
DOI: 10.47852/bonviewJDSIS42021530

# Early Detection of Banana Leaf Disease Using Novel Deep Convolutional Neural Network

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**Abstract:** One of the most widely grown commercial commodities in India is the banana tree, which has important cultural and gastronomic significance in tropical and subtropical areas where banana leaves are widely used for food delivery and packaging in a variety of cultures. Regrettably, the incidence of diverse ailments that damage banana leaves present a significant risk to total output, therefore having an instant effect on the country's economy. To meet this issue, more efficient monitoring systems must be put in place, and control techniques for early illness and pest detection must be developed. Using pest indicators makes this proactive strategy easier. With the successful use of these approaches in a variety of industries, recent advances in agricultural technology have seen the incorporation of deep convolutional neural networks (DCNN) for disease identification in numerous crops. This study's main goal is to put into practice a DCNN that is especially designed to anticipate various illnesses and pest occurrences in banana leaves. Through the use of DCNN, farmers may get vital insights to apply fertilizers sparingly during the early phases, hence preventing the advent of leaf diseases. Remarkably, the suggested approach, which uses a convolutional neural network (CNN) for accurate banana leaf disease detection, exhibits an astounding 99% accuracy when compared to other deep learning techniques. By offering a reliable and precise technique for predicting pest and disease in banana crops, this study advances agricultural practices. The use of state-of-the-art technologies, like CNN and DCNN, highlights the potential revolutionary influence on disease control in banana farming, promoting increased yield and sustainable farming methods.

**Keywords:** deep convolutional neural network, disease prediction, fertilizers

## 1. Introduction

For most developing countries, agriculture is their main source of income, and the banana sector is one of the most important in the world of agribusiness. Three separate genera comprise the Muscaceae family: Musa, Musella, and Ensete. Bananas are members of the genus Musa, and they have been grown for a very long time in many different forms all over the globe. They have several uses in the food sector and alternative health. Several in vitro studies, clinical trials, and animal model testing have highlighted the therapeutic properties found in different sections of bananas [1]. These properties make them potential treatments for conditions such as diabetes, high blood pressure, cancer, ulcers, diarrhea, urolithiasis, Alzheimer's disease, and infections. Additionally, bananas find applications in medical fields like surgical dressing, pain therapy, nanomedicine, pollution control, apoptosis, and the cell cycle. India is the world's largest producer of bananas, followed by China and Indonesia, according to the Food and Agriculture Organization of the United Nations [2]. Agribusiness data indicate that the Philippines, Argentina, Ecuador, and Indonesia are significant contributors to the world's

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agricultural output, making up over 20% of total production. In spite of this, smallholders control an astounding 85% of farms worldwide [3]. These farmers face a variety of biotic and abiotic obstacles. Bananas are the most important fruit and a basic food in the Asia-Pacific area. However, a number of pests and illnesses have been linked to significant productivity losses in producing regions [4]. This emphasizes how urgently comprehensive plans and solutions are needed to lessen the negative effects of these issues on banana farming, protect smallholders' livelihoods, and guarantee the long-term viability of this vital industry. Crop damage brought on by previously infected plant diseases, bacteria, fungus, roundworms, and nutritional deficiencies resulting in lower agricultural productivity and worse quality [5]. It also kills the plant, reduces farmer earnings, and raises production expenses during the control period. However, black leaf stripe diseases, also known as black Sigatoka disease or BLSD, are brought on by the fungus Pseudocercospora fijiensis and have a significant impact on banana yield. BLSD is usually regarded as the deadliest of the several deadly diseases that threaten bananas worldwide [6]. After BLSD's biotrophic phase, a necrotrophic stage with overt symptoms occurs. According to Bhuiyan et al. [7], the illness results in a reduction in chlorophyll production in the photosynthetic portions of the leaf, which affects the structure of banana leaves. The early indications of the illnesses are little black dots on the leaf surface that later develop into thin, brown lines 2 to 3 mm long. The adaxial surface of affected leaves also displays similar lines [8]. The early signs of necrosis are shown by the stripes eventually becoming black and merging together as the illness progresses. Defoliation and early fruit ripening are caused by dead leaves that have dried up. The banana plant's leaves display signs of many illnesses to which it was susceptible [9]. Streak Virus, Panama Virus, Black Sigatoka Virus, Yellow Sigatoka Virus, and Banana Bunchy Top Virus are the names of these diseases. The biotrophic phase, also referred to as the absence of symptoms, may last for many weeks. According to Bhuiyan et al. [7], banana plants may have already sustained severe damage before the illness's first symptoms appear, which might result in production losses of up to 85% [10]. Weeks may be used to quantify damage to banana plants. One hundred percent or more of the world's banana export and production might be lost due to illnesses and other climate factors that affect banana plants. Xanthomonas wilt, bunchy top virus, fusarium wilt (also called Panama wilt), and black Sigatoka are the four main illnesses that may affect bananas. Thus, the first and most important step in the process is the early detection of diseases and pests in the field [11]. Agricultural extension workers are involved in traditional procedures for identifying pests and leaf diseases, but their efficacy is limited in underdeveloped countries owing to a lack of human infrastructure. Asserts that smallholder farmers are unable to handle the challenges of farming successfully because they do not have access to enough empirical data [12]. For farmers, recognizing, evaluating, and managing plant diseases in the fields is an interesting and useful application. To the maximum degree practical, this procedure should be completed as automatically and effectively as possible, at the lowest possible cost. Early detection of pests or agricultural diseases facilitates treatment and reduces adverse effects on food supply chains [13]. Diseases that impact banana crops may be recognized and categorized using an image processing method. It is now feasible to automatically analyses and detect early stages of infection and signs of main banana diseases on leaf surfaces by using computer vision and machine vision technologies. The methods used for image processing are essential to the interpretation of data in this system. Author found that it is important to build intelligent systems that can identify plant ailments based on visual symptoms and external appearances similar to human behavior. An artificial intelligence software for smartphones may be able to provide farmers with early warnings, speed up illness diagnosis, and perhaps stop the spread of diseases and pests. As a result, the importance of early plant disease identification is highlighted. This research constantly places a great deal of focus on deep learning methodologies. Additionally, this study provides a solid foundation for a great deal of possible future research that will examine the whole history of the banana. This study's main goal is to use a deep convolutional neural network (DCNN) to forecast various illnesses and pests that harm banana leaves. By offering early diagnosis, the DCNN acts as a model to assist farmers, enabling them to apply the necessary fertilizers as soon as leaf diseases appear. This proactive strategy helps to both avoid and lessen the effects of illnesses on banana crops. This study's framework is set up as follows: A variety of cutting-edge techniques for banana leaf disease prediction models are covered in Section 2. The operation of the suggested model for the identification and categorization of leaf diseases is described in Section 3. Next, the experimental findings and discussion are presented in Section 4, and the Conclusion is presented in Section 5.

## 2. Related Work

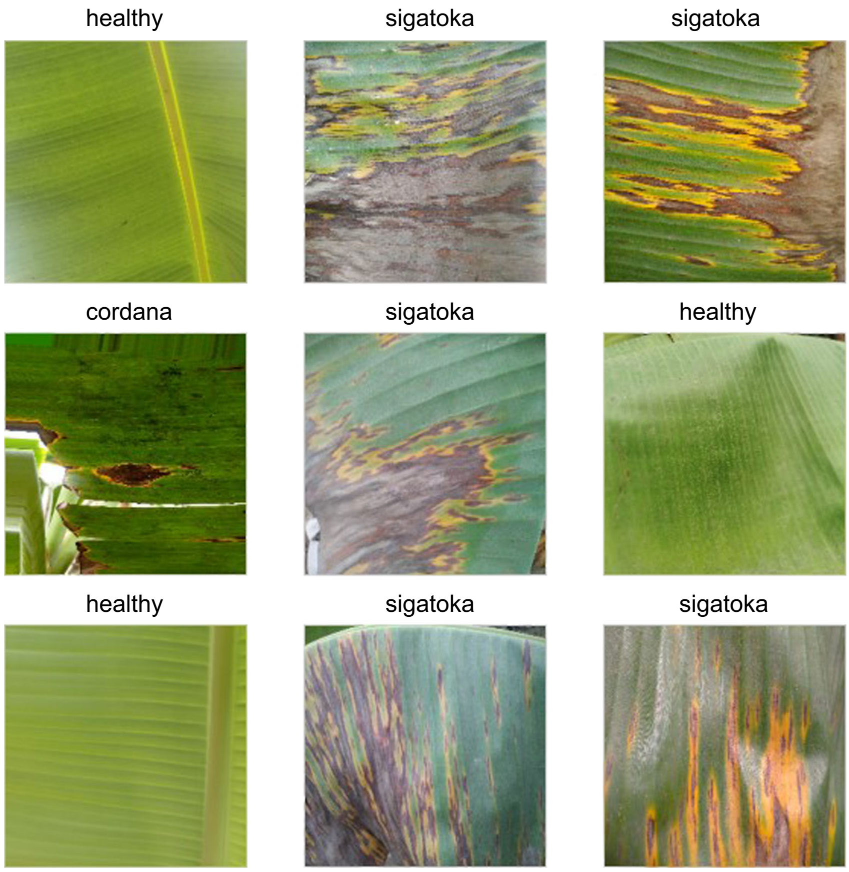
Plant disease detection systems that are automatic use photos of afflicted leaves as input to provide an accurate diagnosis of the illness. The system employs two distinct feature extraction techniques: first, it takes pictures of diseased leaves and processes them using image processing techniques to extract data from them. Using an image processing technique, features including texture, shape, color, histogram of gradient (HOG), SURF, and many more are retrieved. The HOG is used to provide information in the leaf disease diagnostic system developed by Arman et al. [10]. In order to detect plant diseases, author used textural and gradient data in conjunction. They examine several different feature selection algorithms by applying them to a dataset comprising turmeric crop data. The author claims that feature selection using the Information Gain technique and SVM produces superior levels of success in this study including principal component analysis (PCA), Information Gain, and Relief-f attribute methods. For the research done by Aliff et al. [14] to identify diseases affecting banana leaves, the image processing method is advised. Their RGB color models are acquired and then transformed into HSI color models. The HSI picture is then subjected to preprocessing, threshold-based image segmentation, and histogram equalization [15]. Three more classifiers are then compared to the classification: PCA, support vector machines, and backpropagation neural networks. The author developed a method for identifying leaf disease with an 89% accuracy value by using the SVM classifier and the Gabor wavelet transform to extract features. It is suggested in Probojati et al. [16] to use an artificial neural network for the detection and classification of banana leaf disease. The picture is first acquired and pre-processed in the suggested technique, after which the color and Histogram of Template feature are retrieved. After training the data set using the artificial neural network, grading is done. The query photographs are then assessed based on the total percentage of the affected area. Finally, the picture is categorized based on the kind of illness. Numerous recent research has shown that deep learning techniques may be used to tackle challenges related to agricultural disease diagnosis. The LeNet architecture deep learning model is used by Mduma and Leo [17] to detect banana leaf disease. Deep learning models using LeNet architecture perform well in a wide range of picture conditions, including ones with complicated backgrounds and different sizes and orientations. After 25 epochs, the network stabilizes and achieves a high degree of accuracy. To identify tomato illness, a potent real-time deep learning algorithm is used [18]. To identify leaf diseases, Chowdhury et al. [19] used the Alexnet and Googlenet transfer learning models. DCNNs were used in Devi et al. [20] to identify maize leaf diseases. The deep learning transfer learning and SVM classifier approach are used by Ridhovan et al. [21] for early banana disease detection. In this instance, images obtained by hyperspectral remote sensing are used [22]. The classifiers' overall performance is examined, and the average accuracy is determined using spectral and morphological data. About 96% of cases are detected early, 90% of cases are detected in the middle, and 92% of cases are detected late. The distribution of these percentages is as follows: 96% accuracy is achieved with early detection [23].

## 3. Methodology

Multilayer convolutional neural networks (CNN) are an effective way to extract a large number of picture features. The picture is transformed into a digital image in order to produce a two-dimensional matrix. Subsequently, the corresponding convolutional and two-dimensional matrix undergo de sampling. In order to summarize the presence of features in the input, the CNN will analyze the local components of the input using a series of filters. To create the feature map, different sized convolutional kernels or filters are used to gain different picture attributes. The kernel size step size might be the cause of the information loss. Each neuron in the convolutional layer receives just a tiny portion of the outputs from the previous layer after they have been convolved using a "kernel." A neuron's "receptive field" is the range of output values that it is capable of seeing. The second main component is called the "pooling layer." From each group of the outputs from the previous layer, it produces a single neuron. Commonly used pooling methods include max pooling and average pooling. A unique procedure called pooling is used to minimize the dimension of the feature map and is useful in the implementation of downsampling in CNNs. More discriminative and practical characteristics are progressively added to the layers. The layers reduce the spatial complexity of the employed parameters and solve the overfitting issue. CNN is composed of eight convolutional layers and eight pooling layers in this case. The normalization layer is employed in between to improve training and reduce the network's reliance on initialization. Normalization is applied to the gradient values that traverse the network. An average pooling layer averages the input data by taking the mean. Figure 1 depicts the sample leave for the banana leafe dataset.

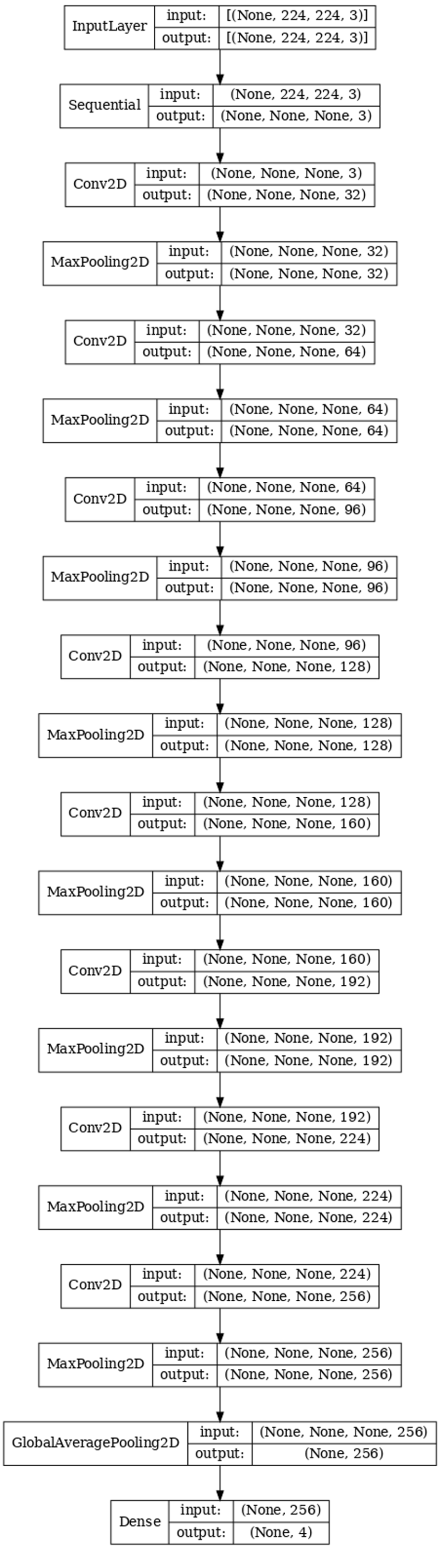
Specific parameters are assigned to each layer in the CNN architecture that has been discussed. Convolutional layer 1 (Conv 2D1) has 32 filters with a $3 \times 3$ filter size, a stride value of 2, and no padding. The pooling layer (Pool1) then applies a $2 \times 2$ filter with a stride of 1. This pattern is repeated in the second convolutional layer (Conv 2D2), with a stride value of 2 and a filter size of $3 \times 3$. There are 64 filters in total. A $2 \times 2$ filter with a stride of 1 is maintained by the equivalent pooling layer (Pool2). With a gradual rise in the number of filters (256) in the final

**Figure 1**
**Sample leaves for the banana leaf dataset**



convolutional layer, this convolutional and pooling process is carried out via Conv 2D8 and Pool8. The neural network design facilitates hierarchical feature extraction and spatial reduction via the use of stride values of 1 for pooling layers and 2 for convolutional layers, in addition to alternating padding values of 0 and 1. The layered structure of the DCNN model is seen in Figure 2. The input picture was sent as a tensor with width, height, and channel dimensions of 224 × 224 × 3 to the DCNN model. Because it and the CNN layer share an input and an output tensor, the sequential layer is chosen. Eight convolutional layers were followed by the addition of a max pooling layer. The feature dimensions were compressed using max pooling with a stride of 1. The most recent max pooling layer provided input to the global average pooling layer, which averages each feature map across its spatial dimensions. This reduces the dimension number of the model and avoids overfitting. Following the global average pooling layer, the output is linked to an output layer and a fully connected layer, which use the previously learned features to conduct classification. The fully connected layer's neuron count is based on the number of classes in the classification job, and the output layer generates the network's final classification result. The DCNN model architecture is generally well suited for image classification tasks, where the goal is to identify the objects contained in the input picture. A paradigm change in agriculture is brought about by the use of DCNN for disease detection, especially in the context of banana leaf diseases. In contrast to conventional techniques, DCNNs provide unmatched precision by identifying complex patterns in pictures and guaranteeing accurate illness detection. Real-time or almost real-time illness diagnosis is made possible by DCNNs' automated analytical capacity, which speeds up the detection process and is essential for prompt action. DCNNs are skilled at identifying novel disease strains because to their flexibility and learning capacities, and the non-intrusive nature of image analysis lowers the possibility of further contamination during detection. Once taught, DCNNs' cost-effectiveness and ability to provide data-driven insights make them a transformational tool for farmers, encouraging proactive management, early diagnosis, and eventually improved crop health.

**Figure 2**
**Proposed multi-layered DCNN architecture**




## 4. Results and Discussion

This section presents the results of a comprehensive examination of the importance of the findings on the early identification of banana leaf disease using the innovative DCNN.

The dataset distribution for different classes is shown in Table 1, where each row represents a distinct category. The number of

**Table 1**
**Data description of classes**

| | | Training images | | | |
|---|---|---|---|---|---|
| ID | Name | Real | Augmented | Validation | Testing |
| 1 | Cordana | 86 | 1000 | 22 | 22 |
| 2 | Healthy | 134 | 1000 | 22 | 22 |
| 3 | Pestalotiopsis | 131 | 1000 | 22 | 22 |
| 4 | Sigatoka | 422 | 1000 | 22 | 22 |

**Table 2**
**Deep convolutional neural network (DCNN)**

| Parameters | Conv 2D1 | Pool1 | Conv 2D2 | Pool2 . . . | Conv 2D8 | Pool8 |
|---|---|---|---|---|---|---|
| Size of filter | 3 × 3 | 2 × 2 | 3 × 3 | 2 × 2 | 3 × 3 | 2 × 2 |
| Filters used | 32 | | 64 | | 256 | |
| Stride_value | 2 | 1 | 2 | 1 | 2 | 1 |
| Padding | 0 | 1 | 0 | 1 | 0 | 1 |

**Table 3**
**Test result of proposed DCNN layered architecture**

| | TP | TN | FP | FN |
|---|---|---|---|---|
| Leaf rust | 54 | 31 | 0 | 1 |
| Healthy | 52 | 34 | 1 | 0 |
| Leaf spot | 57 | 30 | 0 | 1 |
| Leaf blight | 56 | 36 | 1 | 0 |

genuine photographs used to train the model is shown in the table under "Training images," with Cordana having 86, Healthy having 134, Pestalotiopsis having 131, and Sigatoka having 422 real training images. The number of augmented photos used for validation during the training phase is shown in the "Validation" column; there are 1000 enhanced images for each class. Finally, the number of photos reserved for assessing the model after training is specified in the "Testing" column; for each class, 22 genuine and 22 augmented images are assigned. In order to facilitate a full assessment of the model's performance, this structured representation offers a comprehensive overview of the dataset's composition, comprising actual and augmented photos for training, validation, and testing across multiple leaf disease classes. The research made use of a carefully selected dataset of banana leaf disease classes, such as Sigatoka, Cordana, Healthy, and Pestalotiopsis. To increase the model's resilience, the dataset included 88 enhanced photos in addition to the 768 original images, as shown in Table 2. Table 1 illustrates the remarkable precision of the DCNN model in recognizing disease classes and differentiating between healthy leaves.

With an average accuracy of 0.99, Table 3's performance metrics for the DCNN model demonstrate excellent accuracy

**Figure 3**
**Training performance and validation performance**

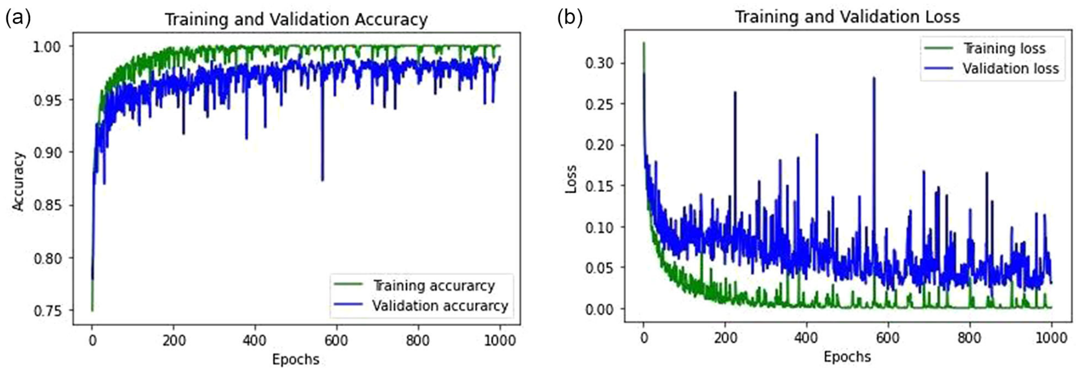



**Figure 4**
**Performance of proposed DCNN**

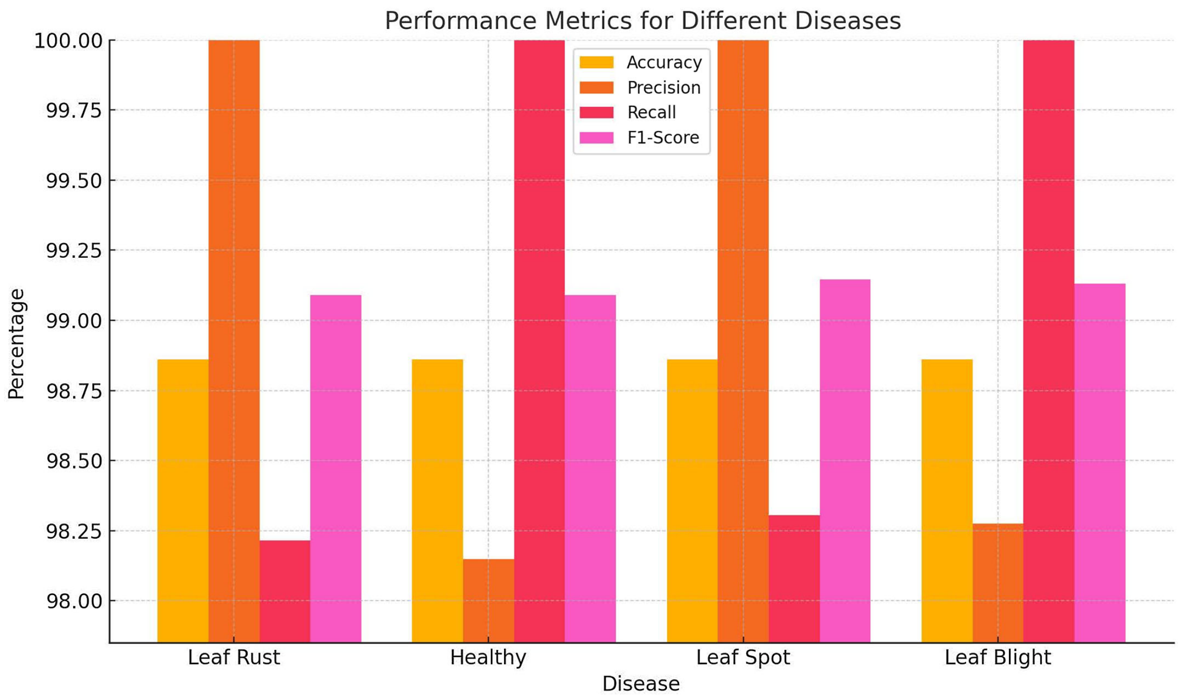


**Table 4**
**Class-wise performance of proposed 8C-DCNN**

| Mode | Acc | Pr | Recall | *F*1-Score |
|---|---|---|---|---|
| Leaf rust | 0.9886 | 1 | 0.9821428 | 0.9909 |
| Healthy | 0.9886 | 0.9814814 | 1 | 0.9909 |
| Leaf spot | 0.9886 | 1 | 0.9830508 | 0.99145 |
| Leaf blight | 0.9886 | 0.9827586 | 1 | 0.99130 |

**Table 5**
**Comparison of proposed DCNN performance with existing techniques**

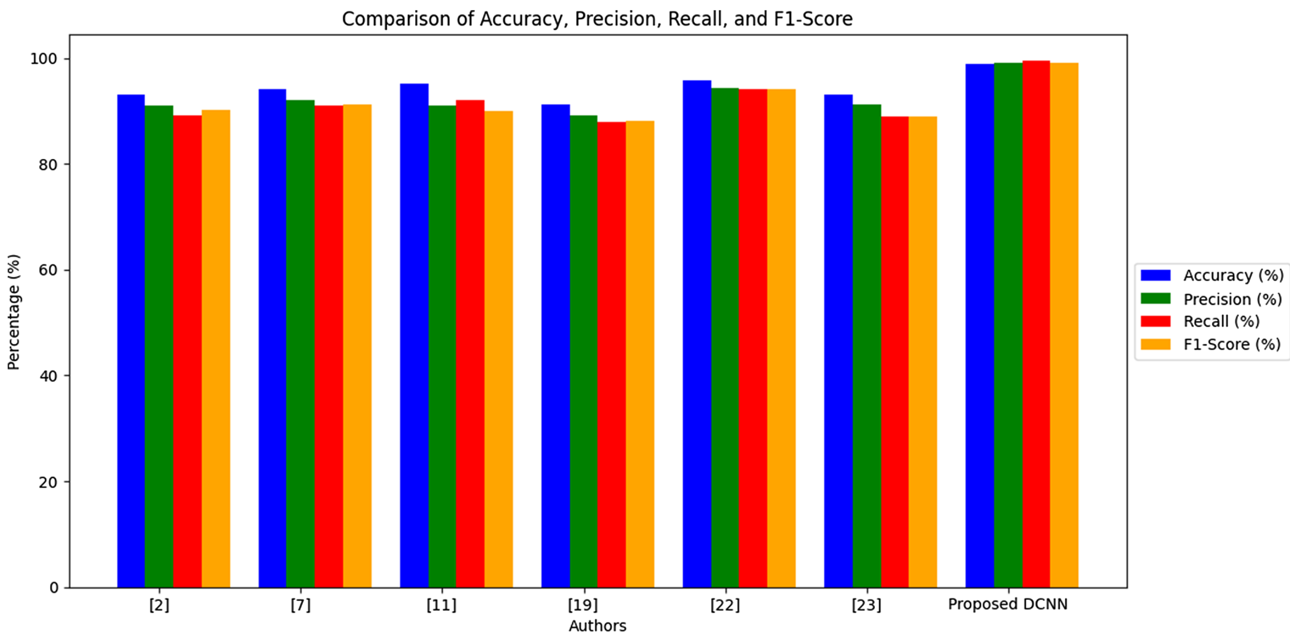
| Authors | Accuracy (%) | Precision (%) | Recall (%) | *F*1-Score (%) |
|---|---|---|---|---|
| [2] | 93.045 | 91.045 | 89.142 | 90.121 |
| [7] | 94.134 | 92.094 | 91.110 | 91.123 |
| [11] | 95.112 | 91.078 | 92.067 | 89.98 |
| [19] | 91.267 | 89.248 | 88 | 88.180 |
| [22] | 95.865 | 94.232 | 94.112 | 94.152 |
| [23] | 93.171 | 91.142 | 88.984 | 88.997 |
| **Proposed DCNN** | **98.92** | **99.13** | **99.43** | **99.113** |

across all classes. Robust precision and recall metrics indicate accurate classification of specific illness groups. *F*1-Scores between 0.991 and 1 demonstrated the model's reliable performance.

The proposed DCNN achieved a high accuracy of 98.92%, outperforming other models in the study. Specifically, the proposed DCNN achieved an impressive accuracy of 98.92%, which surpasses the accuracies of other models reported by various authors. Figure 3 depicts the performance of training and validation. For instance, the model presented by Joshva Devadas et al. [2] reached an accuracy of 93.045%, while the models from Bhuiyan et al. [7], Wan and Yao [11], Chowdhury et al. [19], Chinpanthana [22], and Demilie [23] achieved accuracies of 94.134%, 95.112%, 91.267%, 95.865%, and 93.171%, respectively. Figure 4 shows the performance metrics of various diseases. These results highlight the superior accuracy of the proposed DCNN, which achieved an accuracy of 98.92%. Moreover, the proposed DCNN excels not only in accuracy but also in precision, recall, and *F*1-Score. It achieved a precision of 99.13%, indicating a high level of confidence in the positive predictions made by the model. In comparison, other models reported by the authors had precision rates of 91.045% by Joshva Devadas et al. [2] and 92.094% by Bhuiyan et al. [7]. Additionally, the high recall rate of 99.43% for the proposed DCNN suggests that the model is highly effective in correctly identifying all relevant instances in the dataset. This is notably higher than the recall rates reported by models in Joshva Devadas et al. [2] with 89.142% and in Bhuiyan et al. [7] with 91.110%. The *F*1-Score, which combines precision (the ability to make accurate positive predictions) and recall (the ability to find all relevant instances), further emphasizes the efficacy of the proposed DCNN, with a score of 99.113%. This score indicates that the model has a good balance between making accurate positive predictions (precision) and finding all relevant instances (recall). Table 4 illustrates the class-wise performance of proposed 8C-DCNN. In contrast, the other models exhibited lower *F*1-Scores, such as 90.121% by Joshva Devadas et al. [2] and 91.123% by Bhuiyan et al. [7], underscoring the superior capability of the proposed DCNN in providing reliable and robust predictions. Table 5 represents the performance comparison of proposed DCNNO and existing models. Overall, these results demonstrate that the proposed DCNN outperforms existing models in accuracy, precision, recall, and *F*1-Score, making it a promising solution for tasks requiring high performance and reliability. Figure 5 represents the metrics comparison of propsoed and other existing models.

The result is important for the agricultural industry because it allows for prompt disease management strategies, reduced crop

**Figure 5**
**Comparison of proposed DCNN performance with existing techniques**



losses, and early disease detection. Although the DCNN model for the early detection of banana leaf disease has shown promising results, it still needs to be expanded, transfer learning methods used, and real-time implementation.

## 5. Conclusion

Due to its many applications, banana leaves are essential in the cuisines of many tropical and subtropical nations, which emphasizes the banana tree's significance in India's commerce. That being said, there is a significant problem with the prevalence of banana leaf diseases, which puts the country's economic productivity at risk. In order to curb the spread of illnesses and pests, it becomes imperative to install pest indicators for efficient monitoring and management of these diseases. The apparent efficacy of DCNN in several domains highlights their possible relevance in the area of agriculture. The main goal of this research was to use DCNN technology to anticipate illnesses and pests that affect banana leaves in advance. To lessen the effect of leaf diseases on agricultural output, a proactive strategy is introduced using the suggested DCNN model. One of the main components of this plan is providing farmers with the tools they need to administer essential treatments, including the right fertilizers, at the earliest stages of disease development. Interestingly, the study's results show an astounding 99% accuracy rate, outperforming similar deep learning techniques. The proposed method, which makes use of a CNN, expedites the process of identifying illnesses in banana leaves and produces encouraging results. This development not only protects banana crops but also advances the agricultural industry by using state-of-the-art technologies to improve disease control and guarantee sustained yield.

## Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

## Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

## Author Contribution Statement

**N. R. Rajalakshmi:** Conceptualization, Software, Investigation, Data curation, Writing – original draft. **S. Saravanan:** Conceptualization, Software, Investigation, Data curation, Writing – original draft. **J. Arunpandian:** Validation, Formal analysis. **Sandeep Kumar Mathivanan:** Methodology, Writing – review & editing, Supervision, Project administration. **Prabhu Jayagopal:** Software, Investigation, Resources. **Saurav Mallik:** Methodology, Writing – review & editing, Supervision, Project administration. **Guimin Qin:** Resources, Data curation, Visualization, Supervision, Project administration.

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**How to Cite:** Rajalakshmi, N. R., Saravanan, S., Arunpandian, J., Mathivanan, S. K., Jayagopal, P., Mallik, S., & Qin, G. (2025). Early Detection of Banana Leaf Disease Using Novel Deep Convolutional Neural Network. *Journal of Data Science and Intelligent Systems*, *3*(3), 192–199. https://doi.org/10.47852/bonviewJDSIS42021530