Harnessing PDDC-Net for Efficient Plant Disease Detection and Classification through Deep Learning

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Abstract:

A country's inventive growth is dependent on the agricultural sector. Agriculture, the foundation of all nations, offers food and raw resources. Agriculture is hugely important to humans as a food source. As a result, plant diseases detection has become a major concern. Traditional methods for identifying plant disease are available. However, agriculture professionals or plant pathologists have traditionally employed empty eye inspection to detect leaf disease. This approach of detecting plant leaf disease traditionally can be subjective, time-consuming, as well as expensive, and requires a lot of people and a lot of information about plant diseases. It is also possible to detect plant leaf diseases using an experimentally evaluated software solution. Currently, machine learning and deep learning are using in recent years. This work is focused on implementation of Plant disease detection and classification (PDDC-Net) using deep learning models. The preprocessing operation also performed to remove the different types of noises, which also normalizes the dataset images. Further, the PDDC-Net implements the operation using residual network based convolutional neural network (ResNet-CNN) for feature extraction and classification. Experimental results have shown that proposed PDDC-Net model achieved a good accuracy rate for plant leaf disease detection and classification.

Keywords: Plant disease detection, Plant disease classification, preprocessing, convolutional neural network

1. INTRODUCTION

As a superpower with more than 20% of the world’s total population, China has been facing the problem of insufficient arable land resources. According to the survey data of the Ministry of Agriculture, the proportion of cultivated land in China is even less than 10% of China’s land area. According to statistics data, the mountainous area accounts for about two-thirds of the total land area in China, while the plain area accounts for only one-third. About one third of the country’s agricultural population and arable land are in mountainous areas. This situation has resulted in the relatively poor production conditions of agriculture, forestry, and animal husbandry in China. According to the statistics of the Food and Agriculture Organization of the United Nations, the per capita cultivated land area in China is less than half of the world average level and shows a decreasing trend year by year. Once the natural disasters cause agricultural production reduction, it will seriously affect the output of agricultural products and agricultural development. So how to develop agriculture stably, especially in the complex environment, is extremely important for China.

Although with the development of science and technology, agricultural production is progressing. But due to various natural factors and non-natural factors, the yield of crops has not been greatly improved. Among the various factors, the largest proportion is the problem of crop diseases and insect pests. According to statistics, the area of crops affected by pests and diseases in China is as high as 280 million km2 every year, and the direct yield loss is at least 25 billion kg [1].

At present, the research on crop diseases is mainly divided into two directions. The first one is the traditional physical method, which is mainly based on spectral detection to identify different diseases. Different types of diseases and insect pests cause different leaf damage, which leads to different spectral absorption and reflection of leaves eroded by diseases and healthy crops. The other one is to use computer vision technology to identify images. That is to say, the characteristics of disease images are extracted by using computer related technology, and the recognition is carried out through the different characteristics of diseased plants and healthy plants.

With the rapid development of deep learning [2], especially in image recognition [3], speech analysis, natural language processing and other fields, it shows the uniqueness and efficiency of deep learning. Compared with the traditional methods, deep learning is more efficient in the diagnosis of crop diseases in the field of agricultural production. The deep learning model can monitor, diagnose, and prevent the growth of crops in time. Image recognition of crop diseases and insect pests can reduce the dependence on plant protection technicians in agricultural production, so that farmers can solve the problem in time. Compared with artificial identification, the speed of intelligent network identification is much faster than that of manual detection. And the recognition accuracy is getting higher and higher in the continuous development. The establishment of a sound agricultural network and the combination of Internet and agricultural industry can not only solve the problems related to crop yield affected by diseases and insect pests, but also be conducive to the development of agricultural informatization [4].

2. LITERATURE SURVEY

López et al. proposed an autonomous monitoring system based on a low-cost image sensor that it can capture and send images of the trap contents to a remote-control station with the periodicity demanded by the trapping application. This autonomous monitoring system will be able to cover large areas with very low energy consumption. This issue would be the main key point in this study; since the operational live of the overall monitoring system should be extended to months of continuous operation without any kind of maintenance (*i.e.*, battery replacement). The images delivered by image sensors would be time-stamped and processed in the control station to get the number of individuals found at each trap. All the information would be conveniently stored at the control station, and accessible via Internet by means of available network services at control station (WiFi, WiMax, 3G/4G, *etc.*).

Srivastav et al. focused on a pest control and monitoring system for efficient sugarcane crop production, which is a staple crop grown in Pune. The main pests that affect sugarcane are top shoot borer, stalk borer, rood borer and sugarcane wooly aphid. Apart from this, the main diseases that affect sugarcane crop are red rot, Smut, Grassy Shoot and Wilt. The system uses an acoustic device sensor which monitors the noise level of the pests and gives an indication to the farmer through an alarm when the noise crosses a threshold. The dissemination of is done via a network of wireless sensors connected to a control room computer. Transmission and reception of field data is through ZigBee 802.15.4 digital communication device standard. The system covers large areas with very low energy consumption.

Athanikar et al. described a neural network-based detection and classification of Potato leaf samples using Segmentation of K-Means Clustering. Algorithms are developed to acquire and process colour images of single leaf samples. Different leaves like healthy and diseased are considered for the study. The developed algorithms are used to extract over 24 (colour, texture, and area) features. The texture features are extracted from the gray level co-occurrence matrix (GLCM). A back Propagation Neural Network (BPNN)-based classifier is used to identify and classify the unknown leaf that is the leaf is healthy or diseased, if leaf is diseased, one then classifies the disease by giving description (name, cause, pesticides). The colour, texture and area features are presented to the neural network for training purposes. The trained network is then used to identify and classify the unknown leaf samples. The classification is carried out using different types of features sets, viz., colour, texture, and area. Classification accuracies of over 92% are obtained for all the leaves samples (healthy and diseased) using all the three feature sets.

Wang et al. recognized method to realize plant image diseases, four kinds of neural networks including backpropagation (BP) networks, radial basis function (RBF) neural networks, generalized regression networks (GRNNs) and probabilistic neural networks (PNNs) were used to distinguish wheat stripe rust from wheat leaf rust and to distinguish grape downy mildew from grape powdery mildew based on color features, shape features and texture features extracted from the disease images. The results showed that identification and diagnosis of the plant diseases could be effectively achieved using BP networks, RBF neural networks, GRNNs and PNNs based on image processing.

Samantha et al. proposed image processing methodology to detect scab disease of potato. In this paper first, the captured images are collected from different potato field and are processed for enhancement. Then image segmentation is carried out to get target regions (disease spots). Finally, analysis of the target regions (disease spots) based on histogram approach to finding the phase of the disease and then the treatment consultative module can be prepared by on the lookout for agricultural experts, so plateful the farmers.

Too et al. focused on fine-tuning and evaluation of state-of-the-art deep convolutional neural network for image-based plant disease classification. An empirical comparison of the deep learning architecture is done. The architectures evaluated include VGG 16, Inception V4, ResNet with 50, 101 and 152 layers and DenseNets with 121 layers. The data used for the experiment is 38 different classes including diseased and healthy images of leafs of 14 plants from plant Village. Fast and accurate models for plant disease identification are desired so that accurate measures can be applied early. Thus, alleviating the problem of food security. In this experiment, DenseNets has tendency’s to consistently improve in accuracy with growing number of epochs, with no signs of overfitting and performance deterioration.

Mohanty et al. used a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, in this work trained a deep convolutional neural network to identify 14 crop species and 26 diseases (or absence thereof). The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale.

Dyrmann et al. presented a method that is capable of recognising plant species in colour images by using a convolutional neural network. The network is built from scratch trained and tested on a total of 10,413 images containing 22 weed and crop species at early growth stages. These images originate from six different data sets, which have variations with respect to lighting, resolution, and soil type. This includes images taken under controlled conditions about camera stabilisation and illumination, and images shot with hand-held mobile phones in fields with changing lighting conditions and different soil types. For these 22 species, the network can achieve a classification accuracy of 86.2%.

Sa et al. presented a novel approach to fruit detection using deep convolutional neural networks. The system builded an accurate, fast and reliable fruit detection system, which is a vital element of an autonomous agricultural robotic platform; it is a key element for fruit yield estimation and automated harvesting. Recent work in deep neural networks has led to the development of a state-of-the-art object detector termed Faster Region-based CNN (Faster R-CNN). We adapt this model, through transfer learning, for the task of fruit detection using imagery obtained from two modalities: colour (RGB) and Near-Infrared (NIR). Early and late fusion methods are explored for combining the multi-modal (RGB and NIR) information.

Sladojevic et al. studied the plant disease recognition has been proposed for the first time. All essential steps required for implementing this disease recognition model are fully described throughout the paper, starting from gathering images to create a database, assessed by agricultural experts. Caffe, a deep learning framework developed by Berkley Vision and Learning Centre, was used to perform the deep CNN training. The experimental results on the developed model achieved precision between 91% and 98%, for separate class tests, on average 96.3%.

Ahmeb and Wang proposed a crop disease and pest identification model based on deep learning from the perspective of ecological and environmental protection to solve the problems of many kinds of crop diseases and pests, fast diffusion speed, and long-time of manual identification of diseases and pests. Firstly, crop images are collected by field sampling to collect data set, and image preprocessing is completed by using nearest neighbor interpolation. Then, the network structure of the AlexNet model is improved. By optimizing the full connection layer, different neuron nodes and experimental parameters are set. Finally, the improved AlexNet model is used to identify crop diseases and pests. And the recognition accuracy of this method on other data sets is not less than 91% which has good portability.

Tao and Cuicu studied the aking leaf black spot, anthracnose, and leaf blight of Ophiopogon japonicus as the research objects, lesions were separated by K-Means clustering segmentation technology. PCA (principal component analysis) was carried out on the 46-dimensional eigenvectors composed of color, shape, and texture features, and then the multi-level classifier designed by SVM (support vector machine) was used to identify lesions. The recognition rate of the developed leaf disease recognition system of O. japonicus achieved 93.3%. The results indicated that the system is of great significance to the prevention and control of O. japonicus diseases and the modernization of O. japonicus industry.

Ranjith et al. studied an outline on the major insect pests and the natural enemies associated with wheat. Insect pests and natural enemies in wheat vary from place to place and there are many other insect pests and natural enemies which are associated with wheat ecosystem than those documented during this study. So, further research with in-depth study is recommended so that the role of natural enemies in suppressing the pest population will be helpful for integrated pest management in the wheat ecosystem.

Srinivasan et al. studied to reduce the over-reliance on chemical insecticides, evaluated the effectiveness of microbial pesticides (Bacillus thuringiensis and Metarhizium anisopliae formulations), and neem leaf extract alone and in combination (as an IPM package) against aphids, thrips, and pod borer on yard-long bean in three different provinces of Cambodia from 2015 to early 2018. The bio-pesticides reduced the incidences of thrips (Megalurothrips *usitatus*), and the infestation by the aphid (Aphis craccivora) and the pod-borer (Maruca *vitrata*) to the levels equivalent to chemical pesticide (abamectin) during trials in 2015 and 2016. Hence, the IPM package can be a better alternative to chemical pesticides in managing the key insect pests on yard-long bean in Cambodia.

Toyinbo et al. studied the genetic variability for thrips resistance, estimate heritability of yield and other traits and investigate inter-trait relationships under thrips infestation. One hundred and fifty-six cowpea lines, including one resistant and one susceptible check, were screened for resistance under natural infestation at two locations in Nigeria, in 2016. Test lines were scored for thrips damage weekly for three consecutive weeks, after removal of spreader plants, to obtain damage scores (DS) 1, 2 and 3 while data were collected on agronomic traits. The data were subjected to analysis of variance from which genetic components of the phenotypic variance were computed. Genetic variability among the lines suggests the possibility of genetic control of thrips while number of pods per peduncle, number of peduncles per plant and DS3 would serve as useful selection criteria for thrips resistance.

Authors of [14] developed a mobile software of plant hospital, which could assist users to diagnose lots of kinds plant disease through deep learning technical. An image dataset consisting of 54,306 pictures of healthy or infected plant leaves is used to train a CNN model, to identify 14 kinds of crop species and 26 types of diseases. Authors of [15] did the similar work. They change CNN model to Deep CNN, to increase the ability of plant disease diagnosis and extend the ability of distinguishing plants from their surroundings.

Plants species classification was also attempted to solve by deep learning method. In [16], authors tried to recognize weeds and plant species by CNN model trained with colourful images. A dataset consisting of 10,413 images with 22 weeds and crop species was tested, and the network failed to classify some plant species due to absence of training sample of corresponding species.

A system called DeepFruits was developed to detecting fruit in [17]. The authors use imagery data to detect fruit by CNN approach. To build an accurate, fast, and reliable fruit detection system, they choose the faster-RNN model and made some adjustment [18]. The trained model was able to achieve an improvement of 0.838 precision and recall rate in sweet pepper detection task. They claimed they could complete the entire process of training an annotating a new model per fruit in four hours [17].

At present, the typical convolutional neural networks widely used are as follows.

1) LeNet-5 [19], [20]: Although proposed very early, but LeNet-5 is a complete and successful neural network, especially in handwritten numeral recognition system applications. The LeNet-5 network has seven layers, including two convolution layers, two convergence layers (also called pooling layers), and three full connection layers. The input image size is $32 * 32$, and the output corresponds to 10 categories.

2) ALexNet [21]: AlexNet consists of five convolution layers, three convergence layers and three full connection layers. ALexNet absorbs the idea and principle of LeNet-5 network and makes many innovations. These include using the ReLU function instead of the Sigmoid function to solve the gradient dispersion problem. Dropout is used at the fully connected level to avoid overfitting.

3) Inception Network [22]: Inception is different from the general convolution neural network in that it contains multiple convolution kernels of different sizes in its convolution layer, and the output of Inception is the depth stitching of the feature map. GoogLeNet, the winner of the 2014 ImageNet Image Classification Competition, is the earliest version of Inception v1 used.

4) Residual network [23]: The core idea of residual network is to make a non-linear element composed of neural networks infinitely approximate the original objective function or residual function by using the general approximation theorem. Many nonlinear elements form a very deep network, which is called residual network.

3. PROPOSED SYSTEM

3.1 Crop Disease Recognition Model

Agriculture is one of the most important sources for human sustenance on Earth. Not only does it provide the much necessary food for human existence and consumption but also plays a major vital role in the economy of the country. But Plant diseases have turned into a dilemma as it can cause significant reduction in both quality and quantity of agricultural products. Nowadays farmers are facing many crucial problems for getting better yield cause of rapid change in climate and unexpected level of insects, in order to get better yield, need to reduce the level of pest insect. Several millions of dollars are spent worldwide for the safety of crops, agricultural produce and good, healthy yield. It is a matter of concern to safeguard crops from Bio-aggressors such as pests and insects, which otherwise lead to widespread damage and loss of crops. In a country such as India, approximately 18% of crop yield is lost due to pest attacks every year which is valued around 90,000 million rupees. Conventionally, manual pest monitoring techniques, sticky traps, black light traps are being utilized for pest monitoring and detection in farms. In recent years, deep learning has made breakthroughs in the field of digital image processing, far superior to traditional methods. How to use deep learning technology to study plant diseases and pests' identification has become a research issue of great concern to researchers. Crop disease datasets are pre-processed and uploaded to Residual Network-CNN (ResNet-CNN) for feature extraction. On the other hand, leaf images are also pre-processed and uploaded to ResNet CNN for testing. The leaf images and the crop disease datasets are compared to the trained features which are already trained with the plant diseases. The extracted features have some loss computation and accuracy. The comparison graph could predict the classes of the plant disease.

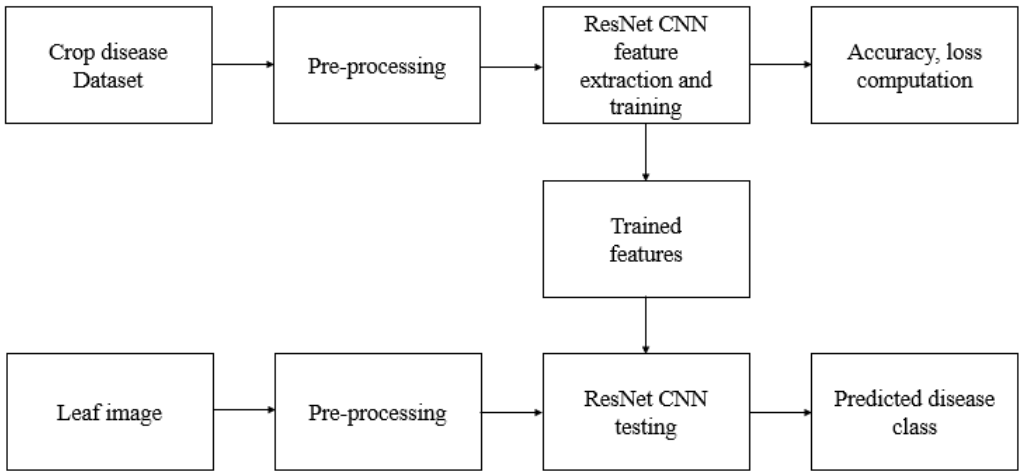

Fig. 1. Block diagram of proposed system.

3.2 Crop disease dataset

The dataset totally contains 15 classes of crop diseases, such as pepper__bell___Bacterial_spot', 'Pepper__bell___healthy', 'Potato___Early_blight', 'Potato___healthy', 'Potato___Late_blight', 'Tomato__Target_Spot', 'Tomato__Tomato_mosaic_virus', 'Tomato__Tomato_YellowLeaf__Curl_Virus', 'Tomato_Bacterial_spot', 'Tomato_Early_blight', 'Tomato_healthy', 'Tomato_Late_blight', 'Tomato_Leaf_Mold','Tomato_Septoria_leaf_spot','Tomato_Spider_mites_Two_spotted_spider_mite. Here, Pepper, Potato, and Tomato are the major crop classes with different disease sub-types.

3.3 Image pre-processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analogue image processing. It allows a much wider range of algorithms to be applied to the input data — the aim of digital image processing is to improve the image data (features) by suppressing unwanted distortions and/or enhancement of some important image features so that our AI-Computer

Vision models can benefit from this improved data to work on. To train a network and make predictions on new data, our images must match the input size of the network. If we need to adjust the size of images to match the network, then we can rescale or crop data to the required size.

There are two ways to resize image data to match the input size of a network. Rescaling multiplies the height and width of the image by a scaling factor. If the scaling factor is not identical in the vertical and horizontal directions, then rescaling changes the spatial extents of the pixels and the aspect ratio.

Cropping extracts a subregion of the image and preserves the spatial extent of each pixel. We can crop images from the center or from random positions in the image. An image is nothing more than a two-dimensional array of numbers (or pixels) ranging between 0 and 255. It is defined by the mathematical function f(x,y) where x and y are the two co-ordinates horizontally and vertically.

Resize image: In this step-in order to visualize the change, we are going to create two functions to display the images the first being a one to display one image and the second for two images. After that, we then create a function called processing that just receives the images as a parameter.

Need of resize image during the pre-processing phase, some images captured by a camera and fed to our AI algorithm vary in size, therefore, we should establish a base size for all images fed into our AI algorithms.

3.4 Proposed ResNet-CNN

Deep neural network is gradually applied to the identification of crop diseases and insect pests. Deep neural network is designed by imitating the structure of biological neural network, an artificial neural network to imitate the brain, using learnable parameters to replace the links between neurons. Convolutional neural network is one of the most widely used deep neural network structures, which is a branch of feed forward neural network. The success of AlexNet network model also confirms the importance of convolutional neural network model. Since then, convolutional neural networks have developed vigorously and have been widely used in financial supervision, text and speech recognition, smart home, medical diagnosis, and other fields.

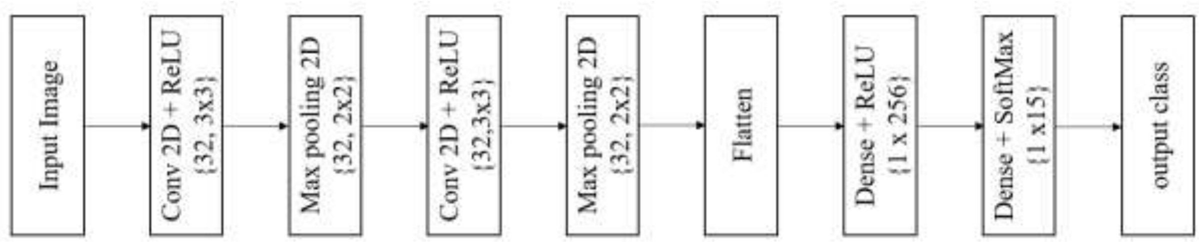

Fig. 2. Proposed ResNet-CNN

Table.1. Layers description.

Layer Names	No. of filters	Kernel size	Feature size
Conv 2D +ReLU	32	3 x 3	62x62x32
Max pooling 2D	-	3 x 3	31x31x32

Conv 2D+ReLU	32	3 x 3	29x29x32
Max pooling 2D	-	3 x 3	14x14x32
Flatten	-	1x6272	1x6272
Dense +ReLU		1 x 256	1 x 256
Dense + SoftMax		1 x 15	1 x 15

Convolutional neural networks are generally composed of three parts. Convolution layer for feature extraction. The convergence layer, also known as the pooling layer, is mainly used for feature selection. The number of parameters is reduced by reducing the number of features. The full connection layer carries out the summary and output of the characteristics. A convolution layer is consisting of a convolution process and a nonlinear activation function ReLU. A typical architecture of CNN model for crop disease recognition is shown in Figure 2.

1) Problem of too many parameters: It is assumed that the size of the input picture is $50 * 50 * 3$. If placed in a fully connected feedforward network, there are 7500 mutually independent links to the hidden layer. And each link also corresponds to its unique weight parameter. With the increase of the number of layers, the size of the parameters also increases significantly. On the one hand, it will easily lead to the occurrence of over-fitting phenomenon. On the other hand, the neural network is too complex, which will seriously affect the training efficiency. In convolutional neural networks, the parameter sharing mechanism makes the same parameters used in multiple functions of a model, and each element of the convolutional kernel will act on a specific position of each local input. The neural network only needs to learn a set of parameters and does not need to optimize learning for each parameter of each position.

2) Image stability: Image stability is the local invariant feature, which means that the natural image will not be affected by the scaling, translation, and rotation of the image size. Because in deep learning, data enhancement is generally needed to improve performance, and fully connected feedforward neural is difficult to ensure the local invariance of the image. This problem can be solved by convolution operation in convolutional neural network.

4. RESULTS

4.1 Modules

1) Upload Crop Disease Dataset: This module is used to select the dataset.
2) Image Processing & Normalization: The image pre-processing and normalization of dataset is achieved by this module.
3) Build Crop Disease Recognition Model: Either selection of trained model or retraining of module is achieved by this module.
4) Upload Test Image & Predict Disease: This module is used to identify the disease class from the test image.

5) Accuracy & Loss Graph: This module is used to plot the accuracy and loss comparison graph various iterations (epochs).

4.2 Results and Discussions

This section gives the detailed analysis of simulation results implemented using "python environment". Further, the performance of proposed method is compared with existing methods using same dataset.

Fig. 3. Sample dataset.

Figure 3 shows the sample images from dataset. Figure 4 In above graph x-axis Figure 4 represents epoch/iterations and y-axis represents accuracy/loss and green line represents accuracy and blue line represents loss and from above graph we can see with each increasing iteration accuracy is getting better and better and loss getting decrease

Fig. 4. Crop recognize as Potato healthy.

Fig. 5. Crop recognize as Potato early blight.

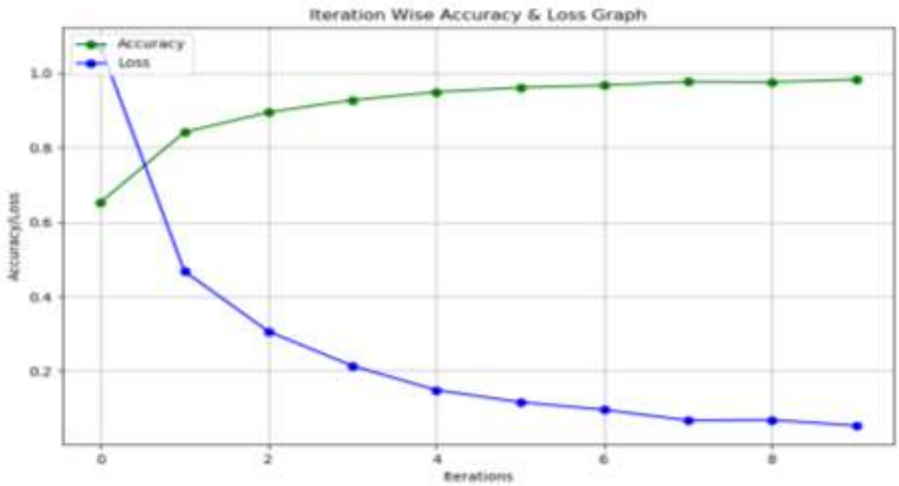

Fig. 6. Iteration wise accuracy & loss graph.

Table 2: Performance comparison.

Method	NB [3]	RF [5]	SVM [9]	Proposed
Accuracy (%)	67.37	77.48	78.37	98.28

Table 2 compares the performance of proposed method with existing methods. Here, Proposed ResNet-CNN resulted in superior Accuracy, as compared to existing NB, RF SVM. The graphical representation of table 2 is presented in figure 6. Finally, the simulations revealed that the proposed ResNet-CNN resulted in superior performance as compared to SVM, naïve bayes, random forest.

5. CONCLUSION

In this work 15 kinds of crop diseases were studied. The model is constructed by using deep learning theory and ResNet-CNN technology. Experiments show that the model can effectively identify the data set, and the overall recognition accuracy is as high as 98.23%. The results show that the recognition accuracy of this hybrid network model is relatively higher than the traditional model, and it can be effectively applied to the identification and detection of plant diseases.

In the future work, there are two directions should be improved, they are extended data set and optimized model. There are 27 diseases with 10 crop species dataset is available, and other species and diseases were not involved, such as rice and wheat, and their related diseases. Therefore, the next step is to obtain more crop species and disease images for research. This model has achieved good recognition accuracy and is worthy of further study and optimization. At the same time, we should design a network model which can classify crop images with higher accuracy.

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