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AI-DRIVEN APPROACH FOR MULTI CROP DISEASE CLASSIFICATION WITH PESTICIDE RECOMMENDATION SYSTEM

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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. The history of using technology in agriculture dates back several decades, but the application of deep learning in crop disease detection gained prominence in the early 21st century with the advent of powerful computing systems and large datasets. In the traditional system, farmers heavily relied on manual observation and knowledge passed down through generations to identify crop diseases. Agricultural experts would physically inspect the crops, diagnose diseases based on visible symptoms, and suggest remedies. While this method had its merits, it was time-consuming, dependent on the expertise of the observer, and sometimes led to misdiagnosis. Therefore, the need for an advanced approach like deep learning in crop disease detection arises from the growing global population and the subsequent increase in food demand. Timely and accurate identification of crop diseases is crucial to prevent significant yield losses. By automating the detection process, farmers can take swift actions to mitigate the spread of diseases, thereby ensuring higher agricultural productivity. Moreover, providing precise pesticide suggestions reduces the environmental impact of farming by minimizing the unnecessary use of chemicals. Deep learning algorithms, particularly convolutional neural networks (CNNs), have proven to be highly effective in image recognition tasks, making them ideal for identifying patterns in images of diseased crops. The introduction of deep learning in agriculture, specifically in crop disease detection and classification, has revolutionized the way farmers manage their crops. By leveraging advanced technologies, farmers can now detect diseases in crops more accurately and efficiently. This has significant implications for food security, as it enables timely intervention and suggests appropriate measures, such as pesticide usage, to curb the spread of diseases.

Keywords: Inventive growth, Food source, Agricultural experts, Yield losses, CNN, Crop management

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,

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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]. In recent years, this problem is on the rise and seriously threatens the development of planting industry. Timely diagnosis and prevention of crop diseases has become particularly important. At present, agricultural workers often use books and network, contact local experts, and use other methods to protect and manage crop diseases. But for various reasons, misjudgements and other problems often occur, resulting in agricultural production is deeply affected.

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

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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%.

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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.

3. PROPOSED SYSTEM

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

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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.

Manual pest monitoring techniques are time consuming and subjective to the availability of a human expert to detect the same. Disease is caused by pathogen which is any agent causing disease. In most of the cases pests or diseases are seen on the leaves or stems of the plant. Therefore, identification of plants, leaves, stems and finding out the pest or diseases, percentage of the pest or disease incidence, symptoms of the pest or disease attack, plays a key role in successful cultivation of crops. In general, there are two types of factors which can bring death and destruction to plants; living(biotic) and nonliving (abiotic) agents. Living agent's including insects, bacteria, fungi and viruses. Nonliving agents include extremes of temperature, excess moisture, poor light, insufficient nutrients, and poor soil pH and air pollutants.

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.

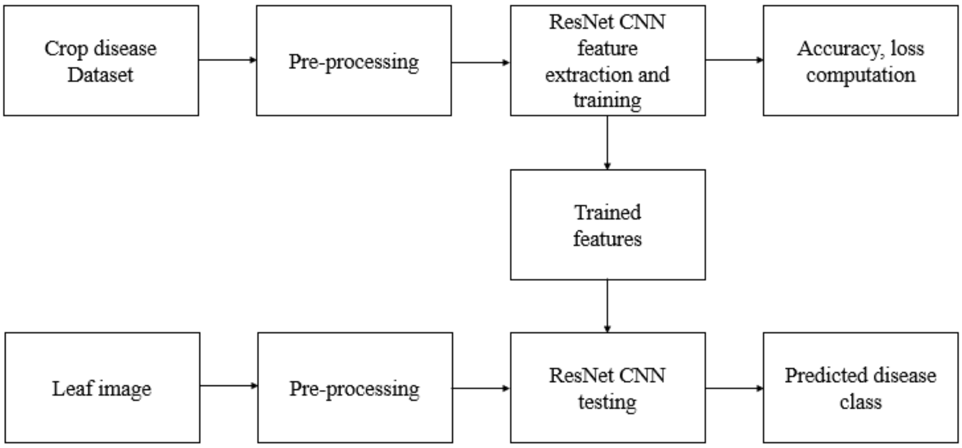

Fig.1: Block diagram of proposed system.

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.

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

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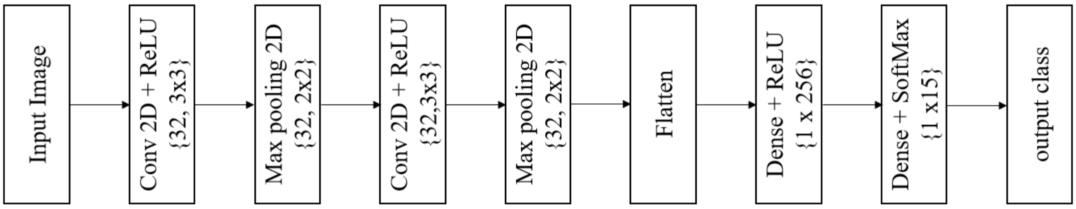

Fig. 2: Proposed ResNet-CNN.

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

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.

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 Fig. 3.2.

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The leftmost image is the input layer, which the computer understands as the input of several matrices. Next is the convolution layer, the activation function of which uses ReLU. The pooling layer has no activation function. The combination of convolution and pooling layers can be constructed many times. The combination of convolution layer and convolution layer or convolution layer and pool layer can be very flexibly, which is not limited when constructing the model. But the most common CNN is a combination of several convolution layers and pooling layers. Finally, there is a full connection layer, which acts as a classifier and maps the learned feature representation to the sample label space.

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from.

Convolution layer is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here d=3 since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F\left(k_x, k_y, d\right)$..

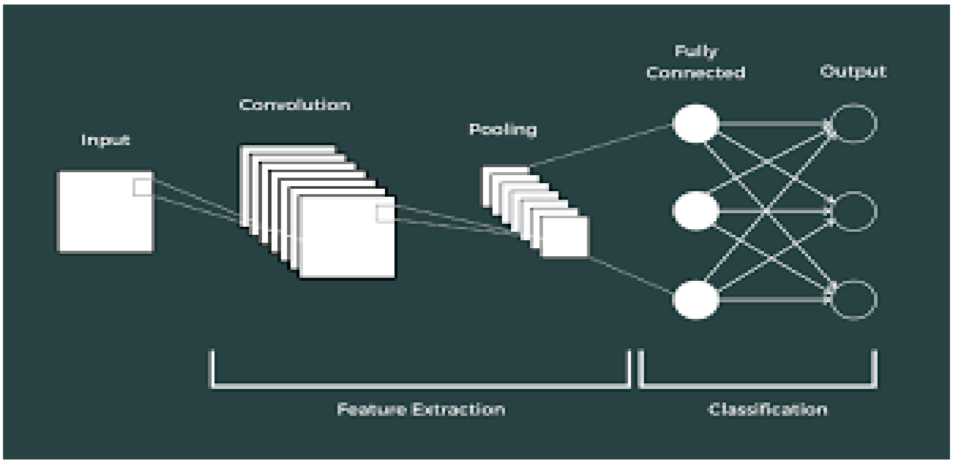

Fig. 3: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.

$$\begin{array}{|c|c|c|c|c|}\hline 1&1&1&0&0\\\hline 0&0&1&1&1\\\hline 1&1&0&0&1\\\hline 0&0&0&1&1\\\hline 1&1&1&0&0\\\hline\end{array} \quad * \quad \begin{array}{|c|c|c|}\hline 1&0&1\\\hline 0&1&0\\\hline 1&0&1\\\hline\end{array}$$

5x5 image   3x3 kernel

(a)

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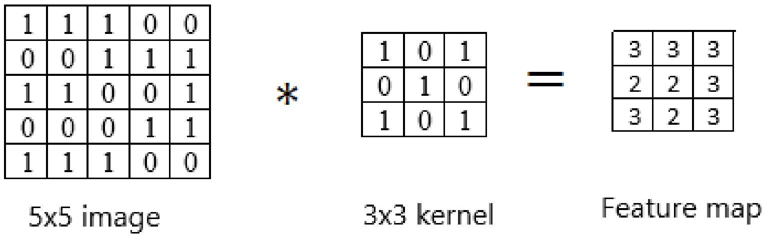
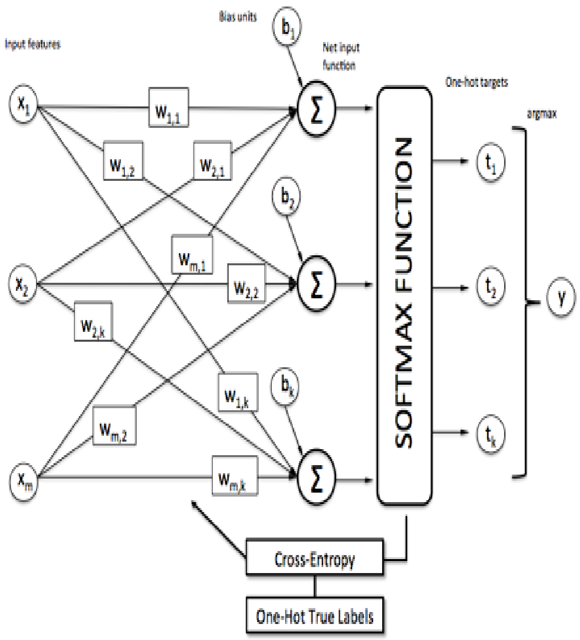


(b)

Fig. 4: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.



Generally, as seen in the above picture softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means

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that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

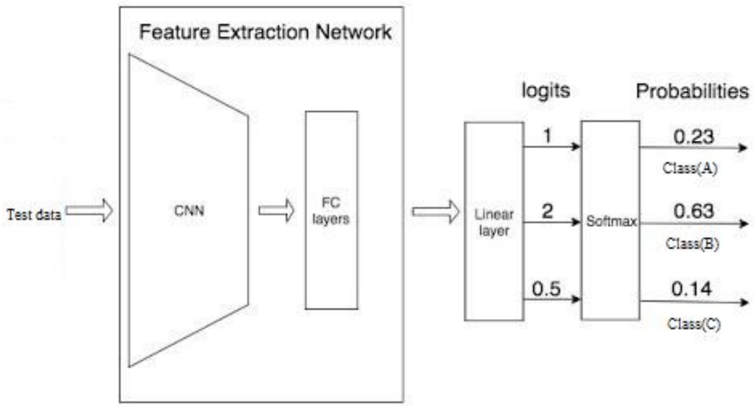

Fig.5 : Example of SoftMax classifier.

In Fig. 5 , and we must predict what is the object that is present in the picture. In the normal case, we predict whether the crop is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding Technique to calculate the cross-entropy loss and get the max. One-Hot Encoding is the technique that is used to categorize the data. In the previous example, if softmax predicts that the object is class A then the One-Hot Encoding for:

Class A will be [1 0 0]

Class B will be [0 1 0]

Class C will be [0 0 1]

From the diagram, we see that the predictions are occurred. But generally, we don't know the predictions. But the machine must choose the correct predicted object. So, for machine to identify an object correctly, it uses a function called cross-entropy function.

So, we choose more similar value by using the below cross-entropy formula.

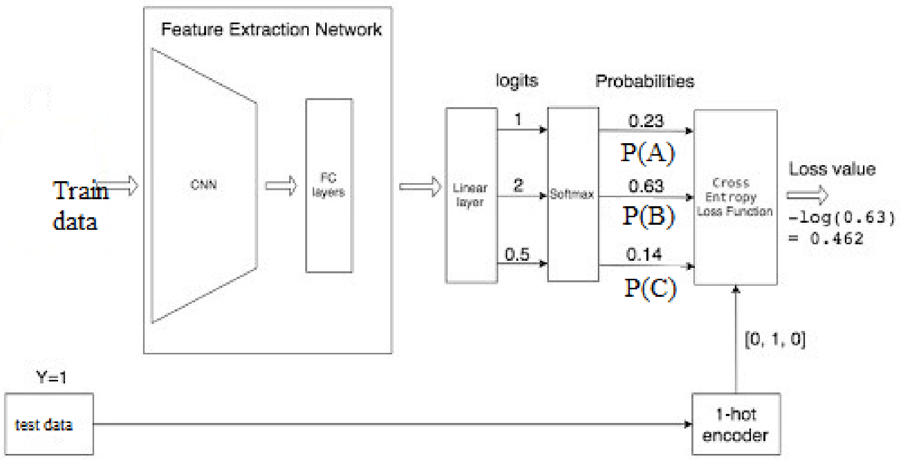

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Fig. 6: Example of SoftMax classifier with test data.

In the above example we see that 0.462 is the loss of the function for class specific classifier. In the same way, we find loss for remaining classifiers. The lowest the loss function, the better the prediction is. The mathematical representation for loss function can be represented as: -

$$LOSS = np.sum(-Y * np.log(Y\_pred))$$

4. RESULTS

In Fig 7 screen we are using 15 different type of crop images and each folder contains images of own leaf and in below screen you can see those image. You too just go inside any above folder to see images, figure 8 is all dataset of leaf's showed.

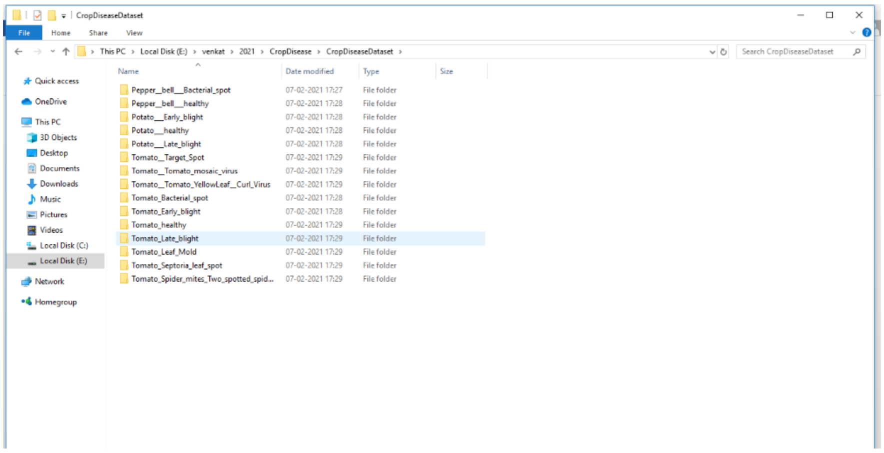

Figure 7: Dataset list

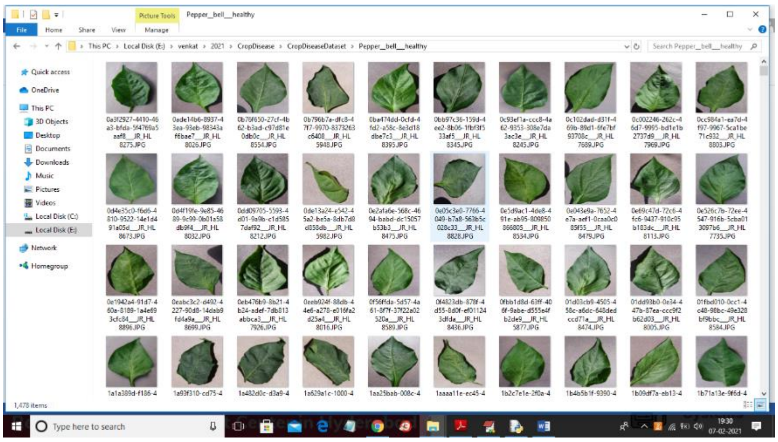

Figure 8: The Dataset

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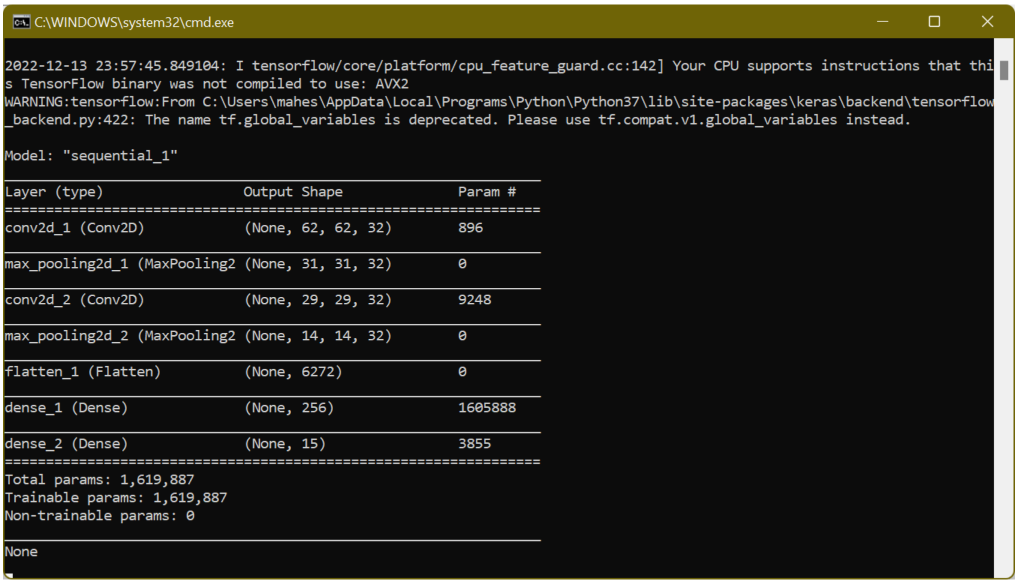

Figure 9: Output After run the model

In above screen we can see we have used CONV2D, MAXPOOLING, FLATTEN and DENSE layer to build crop disease recognition model and RELU details you can see in code

Model	Accuracy
CNN Crop Disease Model	98.27%

Table 1: performance

Table 1 shows the accuracy of crop disease and it is 98.27%.

Figure 10: Output Detected

In above screen potato leaf predicted as healthy and pesticide suggested as no pesticide is required now try with other images

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Figure 11: Output Detected (Tomato Bacterial spot)

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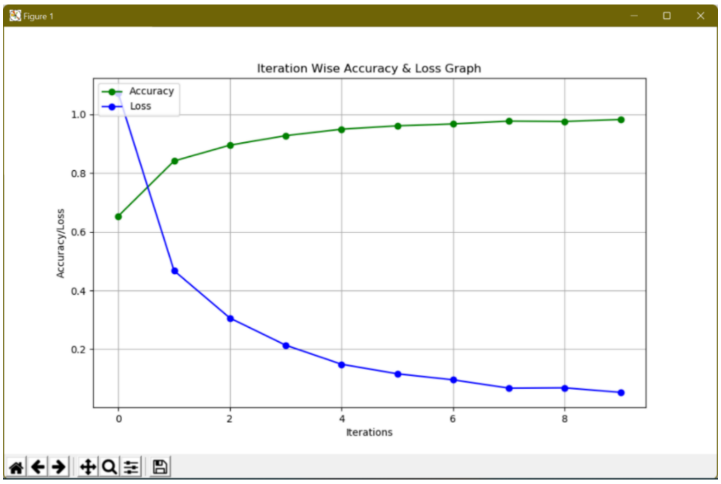

Figure 12: Accuracy & loss graph

In above graph x-axis 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. From above graph we tell our model is very good to predict.

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

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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.

REFERENCES

[1] J. Schmidhuber, ‘‘Deep learning in neural networks: An overview,’’ Neural Netw., vol. 61, pp. 85–117, Jan. 2015.
[2] A.-R. Mohamed, G. E. Dahl, and G. Hinton, ‘‘Acoustic modeling using deep belief networks,’’ IEEE Trans. Audio, Speech, Lang. Process., vol. 20, no. 1, pp. 14–22, Jan. 2012.
[3] Y. Bengio and O. Delalleau, ‘‘On the expressive power of deep architectures,’’ in Proc. 14th Int. Conf. Discovery Sci. Berlin, Germany, 2011, no. 1, pp. 18–36.
[4] L. Deng, O. Abdel-Hamid, and D. Yu, ‘‘A deep convolutional neural network using heterogeneous pooling for trading acoustic invariance with phonetic confusion,’’ in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., May 2013, pp. 6669–6673.
[5] S. Datir and S. Wagh, ‘‘Monitoring and detection of agricultural disease using wireless sensor network,’’ Int. J. Comput. Appl., vol. 87, no. 4, pp. 1–5, Feb. 2014.
[6] O. López, M. Rach, H. Migallon, M. Malumbres, A. Bonastre, and J. Serrano, ‘‘Monitoring pest insect traps by means of low-power image sensor technologies,’’ Sensors, vol. 12, no. 11, pp. 15801–15819, Nov. 2012.
[7] N. Srivastav, G. Chopra, P. Jain, and B. Khatter, ‘‘Pest Monitor and control system using WSN with special referance to acoustic device,’’ in Proc. 27th ICEEE, Jan. 2013, pp. 92–99.
[8] G. Athanikar and M. P. Badar, ‘‘Potato leaf diseases detection and classification system,’’ Int. J. Comput. Sci. Mobile Comput., vol. 5, no. 2, pp. 76–88, 2016.
[9] H. Wang, G. Li, Z. Ma, and X. Li, ‘‘Application of neural networks to image recognition of plant diseases,’’ in Proc. Int. Conf. Syst. Informat. (ICSAI), May 2012, pp. 2159–2164.
[10] D. Samanta, P. P. Chaudhury, and A. Ghosh, ‘‘Scab diseases detection of potato using image processing,’’ Int. J. Comput. Trends Technol., vol. 3, no. 1, pp. 109–113, 2012.
[11] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ‘‘ImageNet classification with deep convolutional neural networks,’’ in Proc. Int. Conf. Neural Inf. Process. Syst. Red Hook, NY, USA: Curran Associates, 2012, pp. 1097–1105.
[12] K. He, X. Zhang, S. Ren, and J. Sun, ‘‘Deep residual learning for image recognition,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2016, pp. 770–778.
[13] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, ‘‘A comparative study of fine-tuning deep learning models for plant disease identification,’’ Comput. Electron. Agricult., vol. 161, pp. 272–279, Jun. 2019.
[14] S. P. Mohanty, D. P. Hughes, and M. Salathé, ‘‘Using deep learning for image-based plant disease detection,’’ Frontiers Plant Sci., vol. 7, p. 1419, Sep. 2016.
[15] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, ‘‘Deep neural networks-based recognition of plant diseases by leaf image classification,’’ in Proc. Comput. Intell. Neurosci., May 2016, Art. no. 3289801.