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# Deep Neural Network based Smart Observation and Disease Diagnosis Expert System for Onion Crop

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**Abstract:**

**Onion crop production is highly affected by diseases such as purple blotch, rust and smut, white tip disease, and downy mildew that affect foliage. The bulbs are often affected by the onion fly, white rot, stem and bulb eelworm, and neck rot. Agricultural information and deep learning are used for quick and accurate diagnosis of diseases in onion plants in this research. An automatic crop monitoring system with an imaging technique is presented where the onion field images are captured periodically for constructing the field monitoring system. The disease symptoms are detected by training the deep neural network model, and the performance of the proposed system is compared with the existing systems. The abnormalities observed in the plant are used for detecting the disease using the forward chaining approach in the proposed system in a real-time environment. The field monitoring system comprises an image logging module, a wireless transceiver, a motor system, and a camera. The deep learning model is trained with a limited amount of infected and healthy onion crops. The ambiguous boundary is used for the primary identification of crop disease symptoms. The proposed model provides a classification accuracy of 96.84% with faster speed when compared to the conventional techniques due to the fewer features used.**

**Keywords:** Neural networks, Deep learning, Farming automation, Transfer learning, Feature visualization, Onion plants, Disease detection.

## 1. INTRODUCTION

Human sustenance is mainly dependent on agriculture. There has been a consistent increase in the cultivation area per farmer recently, leading to challenges in effective crop management. Several farming components and techniques have been computerized over recent years, leading to higher quality and faster production. Automatic monitoring techniques are used in farmlands to manage crop cultivation effectively. The efficiency of the farming processes must be improved to meet the growing demands. The domestic income of several countries is dependent on farming and agriculture. India, Indonesia, Pakistan, Bangladesh, Afghanistan, Turkey, Iran, and other such agricultural nations and their economy are primarily impacted by the growth and quality of the crop. Agricultural productivity defines the economy of such countries [1]. Onion (Allium cepa L.) is the world's second-largest consumed vegetable and is economically valuable. The global market faced a fall in onion prices in February 2020. The trade in India and China, the major onion-producing countries, was affected during Covid19. The onion harvest in Mexico is split into fall and spring, lasting from August to January and March to June [2]. This impacts the demand and supply in America due to the export situation. With no anomalies in weather, there has been a consistency in the cultivation of onions in the United States. With increasing cargo charges, several challenges are faced while moving the product across countries [3].

The onion crop primarily benefits the sustenance of human life. It can be dried and stored for consumption at a later stage when availability is scarce [4]. Onion is used for stimulating hair

regrowth, anti-ageing, anti-diabetic, antiseptic for insect bites, lessening the occurrence of cancer and lowering blood pressure. Over 99 million tons of onion are produced globally, of which India contributes 22.83%, ranked second in global onion production [5]. 25-30 cm seedling gap in flatbed rows and 10-12 cm in fields are provided while cultivating onions. A 10-15 cm gap is given between the rows to generate huge bulbs. To maintain weed-free fields, shallow cultivation and hoeing techniques are followed [6]. Onion planting is often performed by three distinct techniques, namely, planting sets that can be cultivated by the grower from seeds, planting in a seedbed and moving the plants to a field subsequently and planting seeds in the field directly for the crops to mature [7]. The transplanting technique is commonly used for early production.

Efficient management of the large-scale cultivation areas is crucial with the increase in demand for onion. Reduction of the labor force, global warming, crop diseases and several other factors have caused a setback in the management of crops and farmlands. Disease damage has caused a yield loss of over 50% [8], due to which monitoring the growth and disease in onion plants are crucial to minimize yield loss and prevent disease damage. Visual observation and manual monitoring were performed to identify diseases in onion crops conventionally [9]. However, when the area per worker is large, this technique is inefficient and prone to error. Hence, the conventional technique is replaced with the development of an automated, image-based crop disease monitoring and observation system [10]. With the advancements in image processing technology and computer vision system, there has been a massive development in machine learning approaches that can automatically recognize several aspects of images similar to human eyes. Deep neural network (DNN) layer and hierarchical learning approaches of deep-learning (DL) technology [11] are the most effective in visual recognition, autonomous driving, medical applications, multi-image cued story generation, image captioning and several such tasks that involve big data and complex analysis [12-15].

Speech and language detection systems, visual recognition and several other systems rapidly adapt the deep learning technology due to its impressive performance and considerable research advances [16]. Several domains have not considered the use of DNN due to the lack of availability of public datasets. Hence, there is a vast scope for several new research avenues in this domain. Several deep-learning issues, potential solutions and hardware options for plant disease detection and classification that are currently available are discussed here. Several zettabytes of plant leaf datasets are available, and several petabytes of data are included daily. This data had to be labelled with human assistance primarily. However, instantly available labels and supervised learning techniques help classify these large datasets easily [17]. With the increased data size and complexity, unsupervised learning techniques offer a reasonable solution.

Further revision of the current deep learning models is necessary to address issues like data sparsity, missing data, and missing data [18]. Research in deep learning techniques addresses issues such as incomplete, heterogeneous, high-dimensional, unlabeled and low-sample datasets. DNN operates as an inbuilt doubting black box, which motivates the use of unsupervised data in an efficient manner [19]. Noisy and messy data can be handled effectively with several enhanced deep-learning models. The other important challenges for the deep learning models include exploding and vanishing gradients.

**Table 1:** Distribution of onion plants and PDI among various regions of Tamil Nadu

| S. No. | District | Location | Plantation area | PDI |
|---|---|---|---|---|
| 1 | Madurai | Palamedu | 256 acres | 43.86 |
| 2 | Theni | Andipatti | 54 acres | 39.85 |
| 3 | Dindigul | Ottanchathiram | 104 acres | 40.76 |
| 4 | Coimbatore | Navakkarai | 42 acres | 45.63 |
| 5 | Salem | Vazhapadi | 64 acres | 37.65 |

The plant disease index (PDI) among various regions of Tamil Nadu where onion is planted is surveyed and presented in table 1. These diseases can be avoided and arrested in onion plants if early detection and targeted delivery of pesticides can be performed. However, it is challenging for the farmers to do this on large farms.Hence, automation plays a major role in such scenarios. This paper proposes an efficient and accurate deep-learning model for detecting diseases in onion crops. A dataset is created with over 5000 images to train and test the model. Several pre-processing and training methods are used to improve classification accuracy. This system also helps forecast diseases in onion crops along with early detection of the symptoms of suspected diseases, thereby minimizing yield loss caused by infection. The image-based crop monitoring system is automated and consistent.

## 1. LITERATURE REVIEW

Over recent years, several CNN architectures have been developed for identifying diseases in crops based on images. Cascading approach is used in deep learning networks, where each layer computes the gradients or derivatives [20]. There is an exponential increase or decrease of derivatives at each layer. While dealing with the vanishing or exploding gradients, weights increase or reduce based on the gradients. This helps in decreasing the cost function errors. Another commonly observed issue in deep learning models is overfitting. Additional neurons are added to the deep learning networks for challenging issues, making them more complex [21]. During data training, the deep learning network provides more adaptability to the process. However, due to the noise and outliers, there is a possibility of overfitting in this method. While working with real test data, the prediction quality is reduced, and a delay occurs in the training and testing time. In addition to the issue of computational efficiency, achieving maximum throughput while using the minimum volume of resources is a challenge [22]. The current deep learning frameworks need significant computational resources to perform efficiently. This challenge can be addressed with the use of reservoir computing techniques. Offline training while working with medium and large datasets, along with incremental approaches, is another possible solution to this issue [23].

ResNet and DenseNet structures are compared and found to have the same accuracy levels [24]. However, the DenseNet can operate with lesser parameters. Batch normalization, residual learning and non-convolution layers are adopted to improve the prediction phase of the CNN models by researchers. The convolution filter size is reduced to reduce the computational time in these architectures. Hence, compared to AlexNet and VGG, these techniques offer smaller filters [25]. In some scenarios, the dual-stage object detection algorithm RCNN is used [26]. A fully convolutional region proposal network filters the ROI in the faster RCNN models. The ROI pooling network receives the filtered features and performs detection. Accurate and fast extraction is ensured through this technique. The ROI prediction is affected by the quantization issue. A modified faster-RCNN model, the mask RCNN, is used to overcome this issue [27]. This system uses a ResNet–feature pyramid network (FPN) framework. Enhanced semantic segmentation and small object detection are enabled with the FPN technique [28]. The pixel-to-pixel alignment replaces the ROI pooling while considering all computational values of the features.

A single stage object detection model called Yolo is used to predict multiple classes from an input image on a real-time basis without needing a pre-determination process [29]. A cross-entropy function replaces the SoftMax activation function in this model, thereby enabling the detection of multiple classes [30]. Feature extraction is made more robust using this technique, similar to FPN. The darkNet-53 framework is used in this model, which makes it faster than a Single Shot Detector (SSD) [31]. When compared to the Yolo-v3, the RetinaNet offers better performance. This model harnesses an FPN as a backbone classifier. The cases missed during classification are decreased, and the performance of cross-entropy is enhanced by adding a tunable factor in this model [32]. The most commonly used deep learning approaches, the plant species on which they are tested and the performance metrics are shown in table 2.

**Table 2:** Comparison of deep learning approaches in plant disease identification

| Reference | Deep Learning Architecture | Dataset | Plants/ Crop | Estimated Metrics |
|---|---|---|---|---|
| [33] | GoogLeNet | PlantVillage | Tomato, strawberry, soybean, squash, potato, raspberry, grape, peach, corn, cherry, bell pepper, blueberry, apple | 99.35% Classification Accuracy |
| [34] | AlexNet | PlantVillage | Tomato | 95.65% Classification Accuracy |
| [35] | CNN | Bisque platform of Cy Verse | Maize | 96.7% Accuracy |
| [36] | LeNet | PlantVillage | Soybean | 99.32% Classification Accuracy |
| [37] | DCNN | PlantVillage | 14 different crops | 97.22% Accuracy |
| [38] | C-DenseNet | WSRgrading dataset | Wheat | 97.99% Accuracy |

## 2. PROPOSED WORK

A tailored system is designed as a computer program to simulate-expert human problem-solving in a disciplined or narrow domain. This system comprises an end user interface (generating output, receiving input), machine conclusion (basic knowledge analysis) and knowledge base (its heuristics, information etc.). A search technique known as forward chaining is incorporated in this proposed work. This methodology works in such a manner that it starts with known facts; if any of the facts matches with the IF part of the IF-Then rule, that particular rule will be executed.

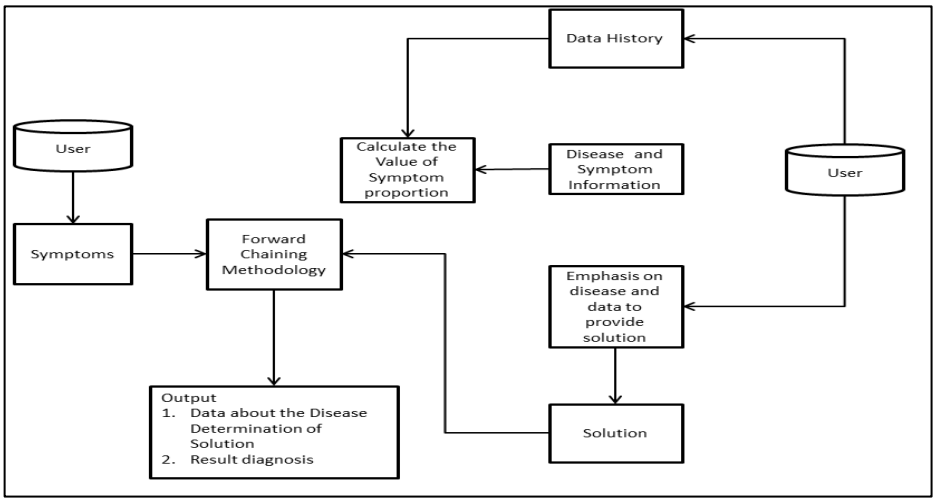



**Fig.1.** Diagnosis of Onion with Expert System

Best First Search, Breadth-First Search (BFS) and Depth-First Search (DFS) are some of the commonly used search methodologies. On execution, this fact will be added to the main database. Every time there is a match, in fact, the process starts from the top rule. It is possible to execute a rule only once. When there are no more executable rules, the matching process ends. Based on the input information, the tracking comments and a conclusion is drawn. The forward chaining method of the approach and the rules that have been produced can be reviewed by experts to be improved or modified to obtain better results. Further, with the help of if-then rules, the facts that match the if the section will enable building the lines between input information and the conclusion. To modify or improve the obtained results, experts can review the proposed rules and approaches with a forward chaining method.

The disease diagnosis process on the onion plants is shown in Fig.1. The database is read to determine the characteristics of the observed data, and a search process is initiated. The user's response must be loaded onto the system based on the features displayed. The following are some of the symptoms displayed, along with the type of disease diagnosed.

- G5: The first step is to check G5 symptoms on the leaves to detect three types of diseases, namely P6, P2 and P1.
- G1: A check is done to detect G1 symptoms, indicating P1 disease.
- G7: A check is done to detect G7 symptoms, indicating the possibility of P2 disease.
- G9: A check is done to detect G9 symptoms, indicating the possibility of P6 disease.

If the symptoms match any one of the above characteristics related to onion disease, the next characteristics will be taken into consideration which will further be diagnosed and based on the responses; the disease will be identified. If the symptom is not identified in the present database, information on the characteristics of the new disease will be obtained from the user. On the other hand, if the system has identified the onion disease solution, the appropriate remedies and conclusions will be displayed for the user.

**Table 3.** Onion Disease Symptoms

| Code | Symptom | Code | Disease |
|---|---|---|---|
| G1 | Dwarf Plant | P1 | Nematodes root cultivation |
| G2 | Leaf spots form a purple zone | P2 | Mosaic virus |
| G3 | Leaf tip dries | P3 | Penicillium reeds |
| G4 | Tubers rot | P4 | Dead shoots |
| G5 | Tuber Tissue dies | P5 | Leaf spots cercospora |
| G6 | Leaves contain spotted curves | P6 | Anthracnose |

| | | | |
|---|---|---|---|
| G7 | Tissue on dead leaf spot | P7 | Leaf spots cercospora |
| G8 | Spotted leaf round and elongated | P8 | Fake flour |
| G9 | Leaf tips pale green spots | P9 | Purple blots |

### 3.1 Datasets:

In this proposed work, a data set comprises 17000 plant leaf images of different sizes obtained from 32 plants which are further categorized into 55 classes. Both cluttered background and clean backgrounds are used in the collected data set. Cluttered background images include the full image of the plant virus isolated leaves in the uniform background is considered for clean background images. Each class carries 50 to 5500 images. There are three categories into which the data set is further divided.

- Category 1 is made up of images with cluttered backgrounds and has 16 classes. These images do not include laboratory-conditioned images.
- Category 2 comprises both cluttered and clean images and has 19 classes. The cluttered images are used for testing, whereas the clean images are used for training.
- Category 3 is made up of 15 classes of images that are cluttered and clean.

  Any data discrepancy is identified based on the variation between the testing data and the training data. To build a robust model, several data augmentation processes were implemented in the image datasets, such as shifts, rotations, random crops, flipping and a combination of these methods. The purpose of data augmentation is to avoid training overfitting. Hence, it is important to test the proposed work with a standard dataset already available for use. The proposed model is tested against CIFAR-10 and MNIST datasets. The CIFAR-10 datasets are made up of about 60,000 images with 10 classes such that every class holds 6000 images in 3x2 RGB format. It has 10,000 test images and 50,000 training images. Here the classes are mutually exclusive. Similarly, the MNIST datasets have a total of 60,000 training images and 10,000 test images with 10 classes of grayscale images with size 2x8.

### 3.2 Benchmarking with standard datasets

The effectiveness of the CIFAR-10 and MNIST datasets is evaluated as the first step. CIFAR-10 and MNIST datasets have been used in machine learning to benchmark computer vision algorithms. 70 to 250 epochs are used from Keras [39] training set to train the network. In this work, all the networks are trained afresh, and a batch size of 20 is used with a Stochastic gradient descent optimizer along with 0.9 as momentum. This methodology holds a learning rate of 0.002 and a decay of 18 e- for each epoch. Data augmentation takes place with real-time reading that loop over data in batches.

## 3. RESULTS AND DISCUSSION

This research focuses on identifying diseases from onion crop images using a deep learning model with expert system. From the experimental results, it was observed that the proposed method was able to show an accuracy of 96.84% for 50 classes of the considered model. It was also obsessed that another model MobileNet could attain an accuracy of 94.06%. However, it is worth noting that these models were still underperforming when compared to VGG by Ferentinos in [40], which attained an accuracy of 95.53%. Similarly, the proposed methodology was also observed to outperform VGG with an accuracy of 31.53% and GoogleNet using transfer learning with an accuracy of 29.8% using the dataset. Table 4 shows the comparison of test accuracy and the number of parameters used for comparison using various models.

**Table4.** Comparison of accuracy using thedataset

| Model | Test Accuracy | Number of parameters |
|---|---|---|
| Proposed Model | 96.84% | 29 |
| MobileNet | 94.06% | 31 |
| VGG | 95.53% | 15 |
| AlexNet | 96.44% | 30 |

Table 5 provides the comparison of the Proposed Model, MobileNet, VGG and AlexNet in terms of specificity, sensitivity, precision, recall and F1-Score. It is evident that the proposed model outperforms the conventional models in these aspects. Fig.2. and Fig.3. shows the observed onion leaves under several perspectives. To test and train the mode, there are two types of images taken into consideration, images with clear background and images with clustered background. It is easier to identify the disease present in the leaf in images with clearer background wherein only one leaf is taken into consideration. The leaf image is first processed and then fed into the database. A comparison of the features of the leaf is made with that of the pre-defined database. Accordingly, a prediction of the disease is made and the user is questioned to further narrow down the disease.

**Table5.** Comparison of other parameters using thedataset

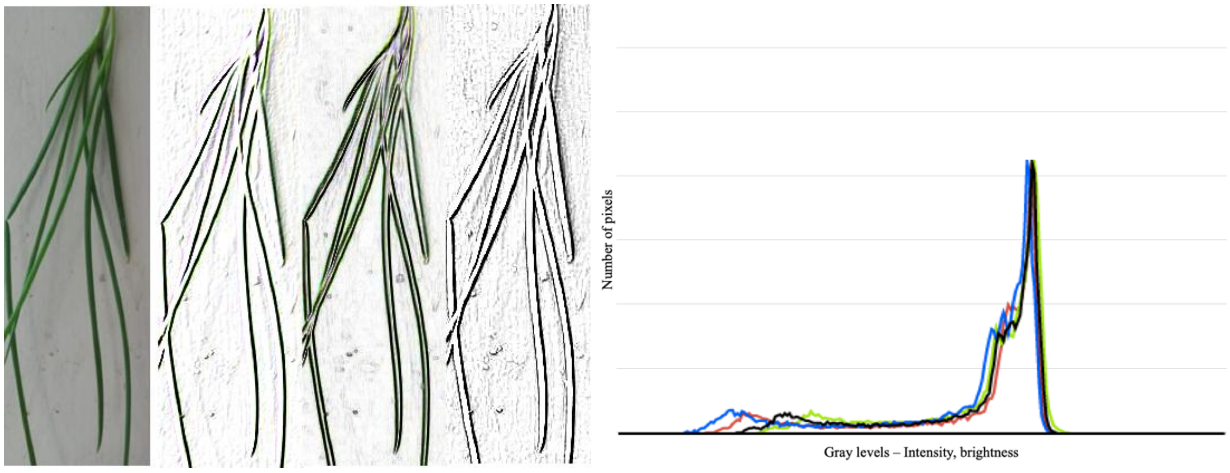
| **Model** | Sensitivity | Specificity | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Proposed Model | 98.97 | 78.89 | 92.76 | 98.93 | 94.17 |
| MobileNet | 98.73 | 57.98 | 82.97 | 98.63 | 90.17 |
| VGG | 98.65 | 34.24 | 74.38 | 98.52 | 85.29 |
| AlexNet | 97.89 | 53.58 | 86.93 | 97.58 | 90.53 |



**Fig.2.**Onion leaves identified with clustered background



**Fig.3.**Onion leaves identified with a clean background




(a) (b)

**Fig. 4. (a)** Original image and edge detection using Robert cross, Sobel-Feldman and Laplacian techniques, **(b)** Histogram of the original image

Figure 4 shows the processing of the sample image with Robert cross, Sobel-Feldman and Laplacian edge detection techniques. The histogram of the image is taken for further processing the image based on the color scales. Figure 5 represents the classification percentage of the data model based on the color features used and the histogram of the image. Here, H represents the hue, S shows the saturation and I is the intensity value. The highest classification percentage observed is 98.6.

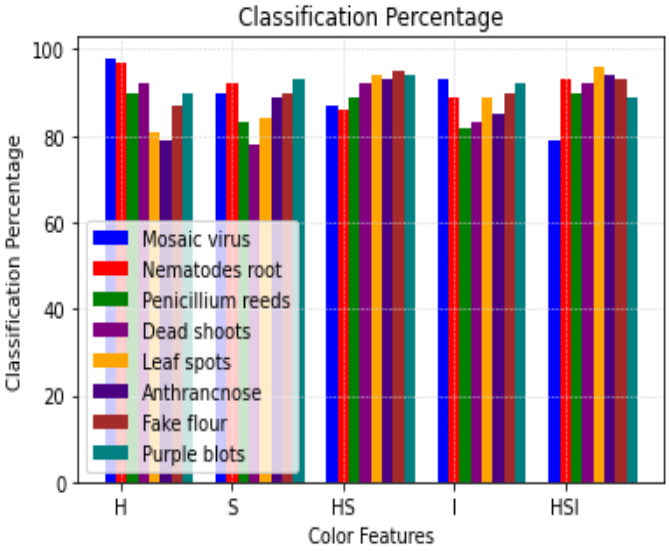



**Fig. 5.** Classification percentage of various diseases

## 4. CONCLUSION AND FUTURE SCOPE

A deep learning model is designed and developed in this proposed methodology using forward chaining. This methodology is used to identify and detect plant diseases in an onion leaf to identify whether it is a healthy or diseased plant. This accuracy of a conventional CNN was matched with the separable CNN model making it the apt model for embedded devices. The proposed model attains a success rate of 96.84% with parameters considerably less than those of the VGG model. Similarly, when compared to N-Adam, Adam and SGD, it is found that the former two have a better convergence rate. Thus, a trade-off between computational cost and accuracy has resulted in the proposed inexpensive model. Based on the training and testing model, it is identified that when images with less clarity and cluttered background are considered, it will result in a higher loss of accuracy. However, the drawback with the proposed methodology is that implementation of this methodology for a large database will prove to be a difficult task. Future work is directed towards improving the performance of the system using a larger dataset and advanced feature extraction techniques while overcoming the trade-off between computational cost and accuracy.

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I would like to acknowledge this manuscript has not been published elsewhere.

**Conflicts of interest**

The authors do not have any conflicts of interest

**Data Availability Statement**

The data used to support the findings of this study are available from the first author upon request [Sahaya Sheela M, email id: hisheelu@gmail.com]

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