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Plant disease identification and pesticides recommendation using Dense Net

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ABSTRACT
Plant diseases, mainly caused by bacteria and fungi, affect crop yield and quality. Detecting disease symptoms at an early stage and promptly is a significant obstacle in safeguarding crops. In developing nations, experts and agronomists commonly opt for visual identification of diseases on vast farms, which incurs both time and monetary expenses. Scientists have suggested diverse deep neural network architectures for recognizing plant ailments. Nevertheless, deep learning algorithms necessitate a vast amount of parameters, which extends the training duration but yields commendable precision. While deep learning and Densenet are widely used in pesticide recommendations. Researchers have suggested diverse deep-learning architectures for detecting agricultural ailments and recommend appropriate pesticides. Test images were diagnosed using an automated Densenet model and the results were verified by plant pathologists. An accuracy of over 92% was achieved in identifying the disease. Our solution is an innovative, scalable and accessible tool for disease management of various crops that can be implemented as a cloud service for farmers and professionals involved sustainable agricultural production.

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Computer Engineering; Computer Science (General); Artificial Intelligence

1. Introduction

As per a statement in the worldwide report presented, populace is expected to witness a significant surge, reaching 9.1 billion by 2050. This surge in the number of individuals will inevitably result in a surge in request for food. However, reduction in arable land, lack in access to uncontaminated water can impede augmentation in food supplies. Thus, there is an urgent need to enhance food output by utilizing minimal cultivation space to cater to the needs of the growing population. The appearance of various irregularities in the crop leads to a significant reduction in both yield and for age quality. Therefore, it is important to identify these crop diseases quickly, as they can hurt farmers 'profits and increase food costs.' Such impacts can cause economic instability in the markets. Furthermore, crop ailments during their unfavorable phases can devastate crops, leading to a famine-like situation in the area, particularly in low-income nations. Usually, experts assist in factory inspections. However, this is a time-consuming and tedious task that necessitates on-site experts. The reliability of current plant testing methods is questionable, and individually testing each plant is a daunting task for humans. Detecting various plant diseases promptly and accurately is crucial to improve the quantity and quality of food and prevent the need for costly spraying methods (Saad & Salman, 2023; Hoang Trong et al., 2020; Ren

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et al., 2019; Krizhevsky et al., 2017). To overcome the limitations of manual procedures, the scientific community is focused on developing automated systems for detecting and classifying plant diseases. Recognizing various types of plant diseases is highly essential and regarded as a crucial matter. Timely identification of crop diseases can facilitate improved agricultural production management by enabling better decision-making. Infected plants typically exhibit specific blemishes or marks on their flowers, leaves, fruits, or stems. Specifically, each infection and Ransomware situation leaves behind distinct designs that can aid in identifying irregularities. Detecting a plant disease necessitates expertise and workforce. Moreover, manually examining to ascertain kind of crop infestation is subjective and takes a lot of time and occasionally disorder seen by cultivator or specialists can be deceptive. It can result in the wrong drug being used when assessing plant diseases, which can affect the quality of the crop and ultimately contaminate nature.

The remaining part of this article is divided into five sections: Section 2 discusses the literature survey. Section 3 presents the system architecture of proposed system. The materials and methods for this study are discussed in Section 4. Section 5 presents the results of the proposed system and Section 6 includes conclusion and future scope.

2. Literature survey

The authors found that the deeper support vector machine (SVM) approach performed better than the transfer-learning equivalent in classifying rice leaf diseases. Statistical analysis showed that the ResNet50 plus SVM depth function performance was good along a 0.9838 of F1 score (Sethy et al., 2020). A developed algorithm designed for the automatic identification and categorization of diseases affecting plant leaves has demonstrated encouraging outcomes. The picture partitioning technique utilizing genetic algorithm successfully identified diseased leaf areas, which were then classified into different categories based on the extracted features. The validation process showed that the algorithm has a high level of accuracy, making it a reliable tool for detecting crop diseases (Butale & Kodavade, 2019). They additionally noticed that the leaf information displayed a multi-tiered depiction, with characteristics progressively converting from less complex concepts to more complex ones that corresponded to classifications of plant species (Lee et al., 2017). The prototype exhibited the capacity to accurately recognize 14 varieties of crops and 26 ailments. The results indicate that deep learning approaches could be an efficient tool for smartphone-based disease diagnosis in agriculture (Farjon et al., 2020). A study found that DL methods are superior to ML methods in terms of disease detection accuracy. The most accurate method proved to be VGG-16 with a CA of 89.5%, followed by Inception-v3 with a CA of 89%. SVM and (Visual Geometry Group) VGG-19 had revenue of 87% and (Stochastic Gradient Decent) SGD of 86.5%. (Random Forest) RF proved to be the least accurate method with an AC of 76.8% (Mohanty et al., 2016).

3. Proposed system

The system architecture for Plant disease identification and pesticides recommendation using Densenet model is shown in Figure 1. Aim of the proposed system is to help farmers to detect plant diseases early and recommend appropriate pesticides for treatment. The system is designed using the Densenet model, a deep-learning architecture that is widely used in image classification and recognition.

The proposed system for plant disease identification and pesticides recommendation using Densenet model has numerous advantages for farmers. By helping to detect plant diseases early, recommending appropriate pesticides, and eliminating the need for manual inspection, this system can help farmers reduce crop losses and increase their yields.

4. Materials and methods

First, The DenseNet-77 architecture, as proposed by Albahli and Nawaz (2022), features a diminished count of model parameters in contrast to the original DenseNet model. Additionally, the structure of each dense block (Db) layer has been streamlined by reducing its size. This results in a flatter model than the Hourglass104 approach, with a total of four dbs. A complete illustration of the DenseNet-77 design showcased in Figure 2. This perspective has fewer model parameters (6.2 million) than the Hourglass104 central network (187 million), making it more IT efficient than the original core network. In every database, the folding tiers are linked in a direct manner, and the attribute charts that are generated from the initial tiers are transmitted to following tiers (Simonyan & Zisserman, 2014; He, 2016; Huang et al., 2017). Dense Net design promotes the usage of computational procedures and improves the transmission of processed data across

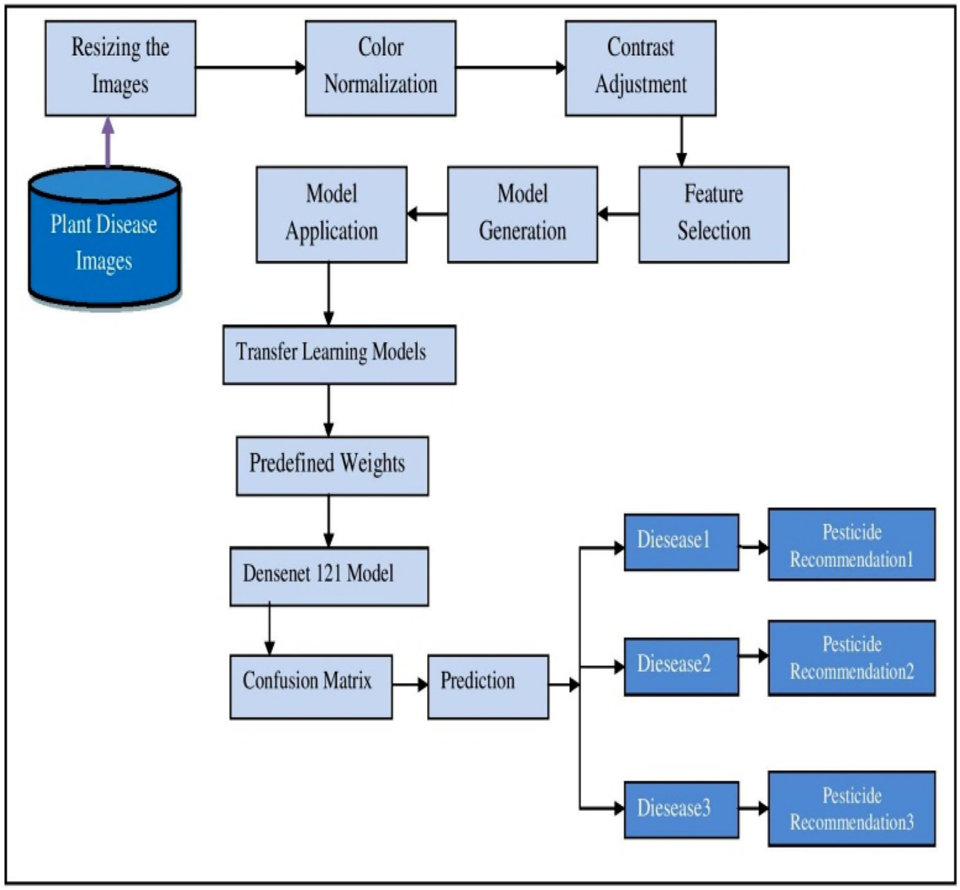

Figure 1. System architecture.

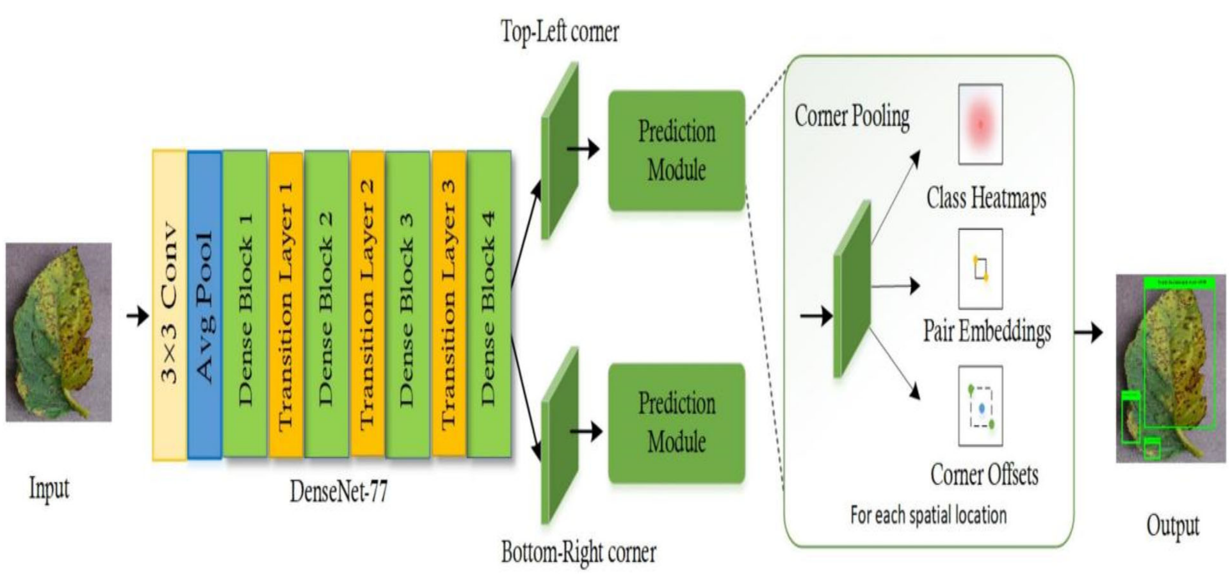

Figure 2. Flow diagram.

the network framework, making it extremely effective in managing image abnormalities.

DenseNet-121 is a model of convolutional neural network that aims to classify images through the use of dense layers featuring compact interconnections (Zhang et al., 2019; Tao et al., 2020; Geetharamani & Pandian, 2019; Chen et al., 2020; Chen & Yuan, 2019; Sharif et al., 2018). In this design, every layer gets supplementary inputs from the layers that come before it and then transfers the resulting feature maps to the subsequent layer. The layers are concatenated, thus enabling the next layer to gain access to the collective knowledge of all the previous layers. Additionally, the matrix is intended to be streamlined and condensed because the characteristic maps of the previous layers are transferred to the subsequent layers. This approach decreases the count of channels in a compact block, and the rate of expansion of a channel is indicated by *k*.

The working mechanism of a compact unit in DenseNet is demonstrated in Figure 3. Every layer of the composition undergoes regularization, activation, and convolution processes to produce output feature maps consisting of *k* channels. The result of the following levels is converted using batch normalization, ReLu activation, convolution, and pooling.

Operating mechanism of a compact unit. The strata exhibit a potent incline movement and a greater assortment of traits. When contrasted with ResNet, DenseNet is petite. Additionally, the classifiers in the ordinary ConvNet pattern manipulate intricate traits, while DenseNet employs all traits, including those with varied complexities, and furnishes unobstructed decision borders.

The DenseNet-77 design is a less heavy variant of the DenseNet lineage that provides two primary advantages compared to the conventional DenseNet. The comparison of dense net is shown in Figure 4.

To address the issue of vanishing gradient, DenseNet-121 enhances the profundity of the convolution neural network (Shi et al., 2017; Simonyan & Zisserman, 2014; Thenmozhi & Srinivasulu Reddy, 2019; Türkoğlu & Hanbay, 2018). The structure comprises of four compact segments, commencing with the first segment that employs filter sizes of 1×1 and 3×3, and is duplicated six times. The second segment iterates the same process with filter sizes of 3×3 and 1×1, carried out 12 times. The third segment executes convolution operations with identical filter size, which are replicated 24 times, while the fourth segment repeats the same steps 16 times. Transition blocks that incorporate convolution and pooling layers are interposed between the Dbs.

4.1. Materials

A thorough discourse on the proposed method for identifying and categorizing leaf diseases is shown here. The primary objective of this framework is to introduce a precise and efficient computational approach that can generate a distinctive set of features automatically, eliminating the need for manual exploration. Our investigation comprises of two crucial phases for the automated identification of illnesses in plant leaves. First, we utilize images from the Plant Village dataset to create annotations that accurately identify stakeholders and their corresponding classes. These annotations are then utilized to train the CornerNet method that is based on DenseNet-77. In the testing phase, we employ pictures from the examination set to verify the effectiveness of the model. To be more specific, we integrate a DenseNet-77 network into the feature extraction component of the CornerNet framework (Chen et al., 2020; Wiatowski & Bolcskei, 2018; Jian & Wei, 2010) for only feature extraction, and for further processing we used DenseNet-121 (Hernandez-de-Menendez et al., 2020; Hernández-de-Menéndez et al., 2022). The fundamental network strategy employed by DenseNet-77 involves the computation of a characteristic vector which is subsequently relayed to a CornerNet model detector operating in a single stage to identify impacted areas and categorize them under 15 distinct classes.

4.2. Process steps

1. Replicating images in order to facilitate the study and prediction of the structure with new and unfamiliar layouts, it is imperative that the images align with the measurements of the

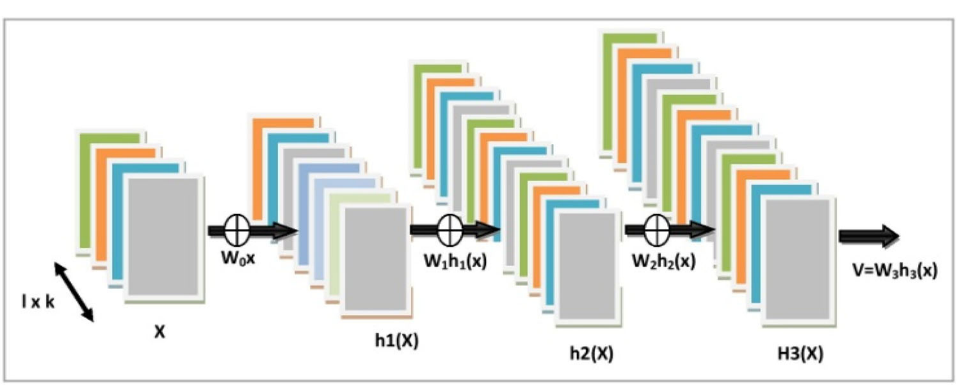

Figure 3. Composition layers.

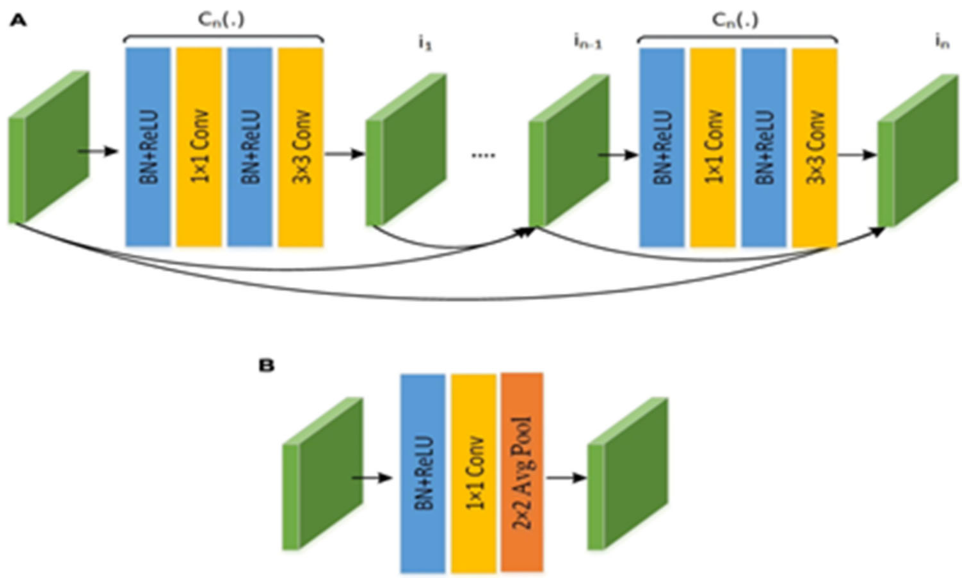

Figure 4. Densenet comparisons of A&B.

input network. If the size of the pictures needs to be altered to conform to the pattern, they can be reduced or cropped to the required dimensions. We created a process that constructs arrays of pictures by saving the pathway to our assortment of images in a variable and subsequently loading directories.

2. Changing the size of images is a critical step in the deep learning procedure since it transforms the raw input data into a format that the network can accept. By altering the image's dimensions to correspond to utilizing the initial layer, we have the ability to ready the visual representation for online use.
3. Applying Gaussian blur – Eliminating irrelevant data, pre-processing of data can improve the intended functionality or eliminate any anomalies that may corrupt the network, making it possible for you to effortlessly standardize or eradicate noise from the input data.
4. Foreground mask generation can be accomplished through Background Subtraction Technique which helps differentiate between foreground entities and the background. This is a widely used method to detect moving objects in the presence of stationary cameras. Object tracking greatly relies on the effectiveness of Background Reduction Techniques.
5. Anti-aliasing is a method of digital image processing that lessens and eliminates image distortion. Typically, selecting the local mean is necessary to accomplish the objective of smoothing in the spatial domain. Three frequently applied smoothing filters are average smoothing, Gaussian smoothing and adaptive smoothing.
6. Turning, mirroring and resizing are common image editing techniques. Turning involves rotating an image by a certain degree. Mirroring, on the other hand, flips an image horizontally or vertically. Modifying the dimensions, commonly referred to as cropping, comprises the act of choosing a distinct section of the initial visual and altering its magnitude to correspond to the initial image.
7. Color grading, Hue modification: method of enhancing image for rectifying and adjusting disparities in its visual perception by the human eye is referred to as color grading. By making some swift modifications, we can digitally modify the image to resemble and evoke the same emotions as we experienced while viewing it in its original form. Hue modification is a phrase that signifies the strength of a color. The term 'brightness' accurately depicts the degree of brightness or dullness of a color. A monochrome or black-and-white picture lacks any hue modification, while a colored image of a sun-drenched field of blossoming flowers can have a high degree of hue modification.
8. Precise Picture Preprocessing comprises diverse methods for readying pictures for DL systems. In previous investigations, reducing the picture dimensions to fifty percent of its original size was a widespread approach for the AlexNet structure and VGG16 network. The technique of partitioning pictures into sections, also referred to as image segmentation, it was utilized to

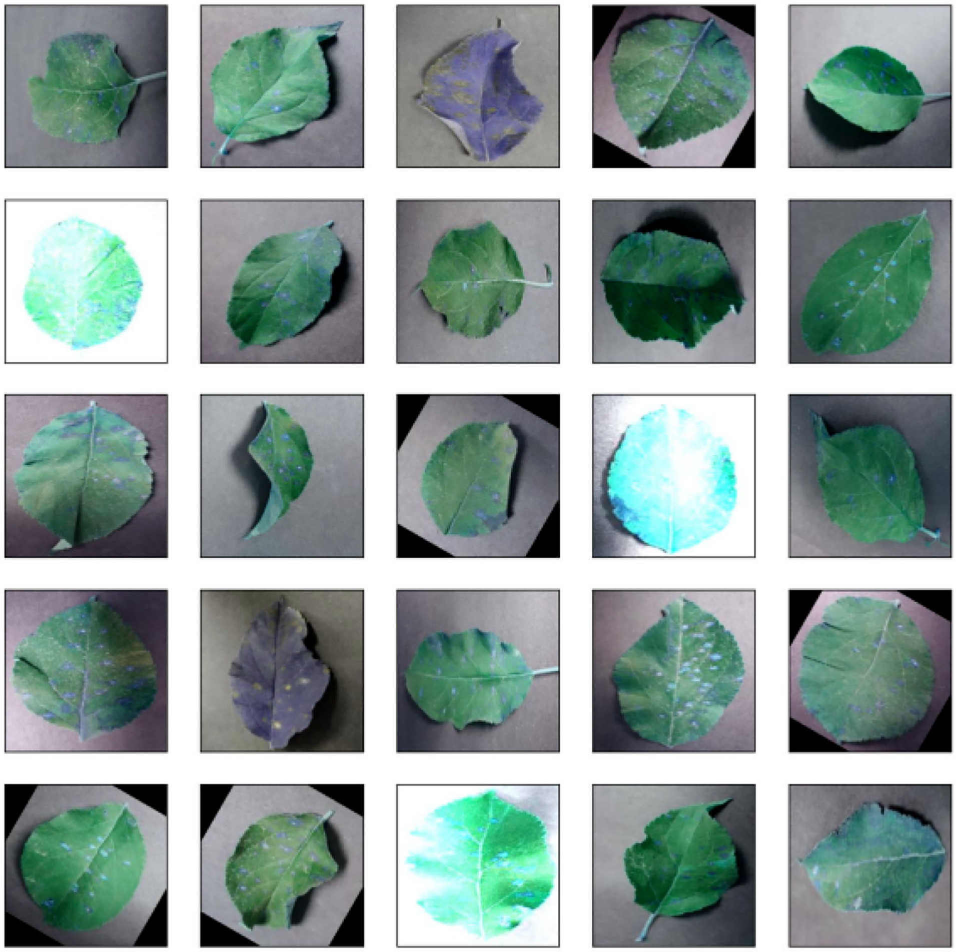

Figure 5. Data sets used.

Figure 6. Extraction of color variations.

enhance the dataset's scope, focus on specific areas, and simplify data for researchers. To accomplish this goal, techniques, such as calyx, stem scar and sill segmentation were utilized. Furthermore, certain datasets utilized adaptive histogram equalization to amplify the quality of the image. It is important to ensure that the proportion of classes in the dataset is balanced for optimal machine-learning model performance. Synthetic minority oversampling methodology and other resampling techniques like IMPS, SMOTE, RUS, and ROS can be utilized to address class imbalance.

9. In the proposed work Adam optimizer was used in the output layer in facilitating the efficient learning and convergence of neural networks toward optimal solutions. Among these algorithms, the Adam optimizer stands out as one of the most widely used in training deep neural networks. Adam optimizer adapts learning rates independently for each parameter, thereby enhancing optimization and convergence, particularly in intricate loss landscapes. The incorporation of bias correction mechanisms helps mitigate initialization bias in the initial moments, promoting accelerated convergence during the early stages of training.

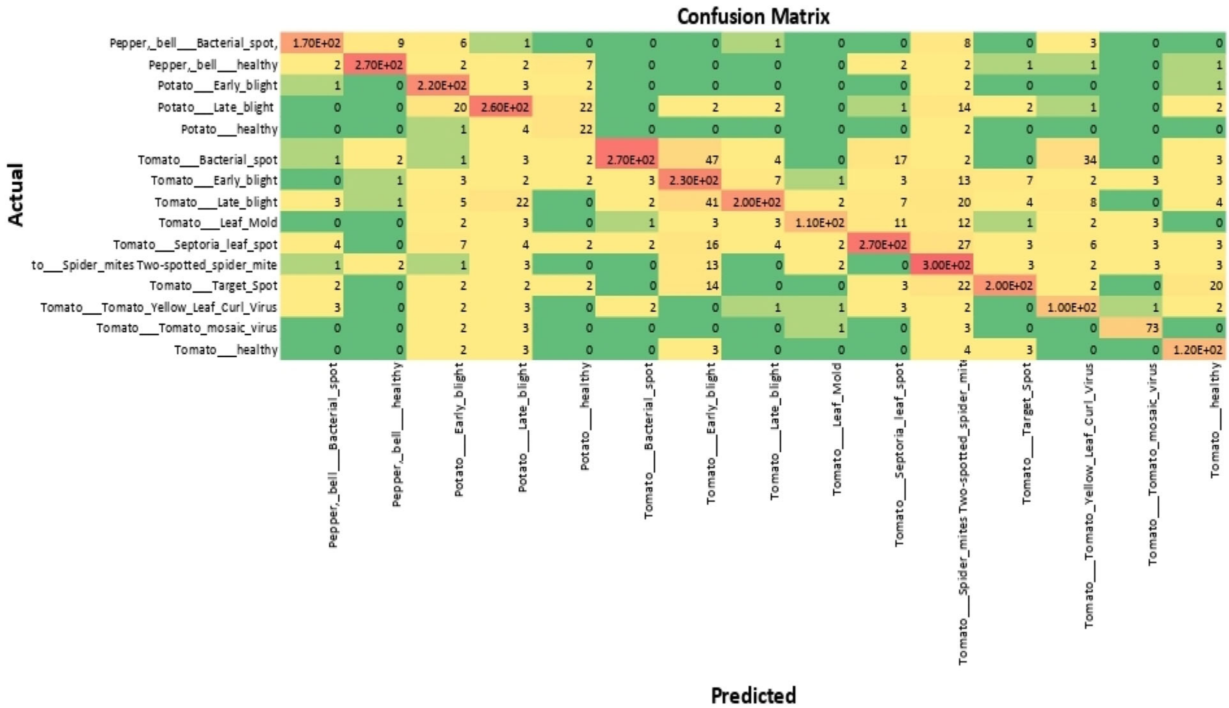

Figure 7. Confusion matrix.

To minimize noise in the dataset, the background can be removed using techniques like function of Gaussian density, technique of thresholding histogram, and algorithm for reducing noise. More tasks involve creating bounding boxes for weed detection, fruit counting, and object classification. Few datasets implement Transformation of image space, for instance, from RGB to HIS color scheme, alternative schemes like HSV.

4.3. Data sets

Dataset for the experimental work collected from Kaggle is shown in Figure 5, it is an open source platform for collecting data. Preparation of data for model training relied on creating annotations for object recognition. The main emphasis was on accurately identifying the impacted area through the training model and its corresponding classification. To achieve this, we initially utilized the Plant Village dataset's (https://www.kaggle.com/datasets/javaidahmadwani/new-plant-village-dataset-test-set) plant sample training images and applied the Label Img tool to produce the necessary annotations. The dataset consisting around 12,486 images pot of which 80% was used for training and 20% for testing. These annotations help to accurately delineate diseased leaf areas by creating a(bbx) bounding box around them. Annotation dimensions are stored in an XML file, which is then used to train the models. Some examples of annotated samples are shown in Figure 6.

These prototypes have been exceptionally beneficial in the domain of image identification since they permit automatic characteristic extraction from feature space of high dimensions, offering noteworthy benefits over conventional manual feature extraction methods. Moreover, with increase in computational power and training samples, deep neural networks are becoming increasingly powerful in characterizing data. The popularity of deep learning has skyrocketed in both industry and academia, with deep neural network models outperforming traditional models. Currently, deep grid of convolutional neural matrix is the most extensively employed framework for deep learning. Results should be clear and concise.

4.4. Mathematical equations

Accuracy:

This metric measures the effectiveness of the approach in identifying the accurate anticipated instances.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \qquad (1)$$

Precision:

Precision is a measure which evaluates effectiveness of a technique for identifying accurate anticipated cases.

```
In [5]: # Plot a histogram
plt.hist(train['DiseaseID'])
plt.title('Frequency Histogram of Species')
plt.figure(figsize=(12, 12))
plt.show()
```

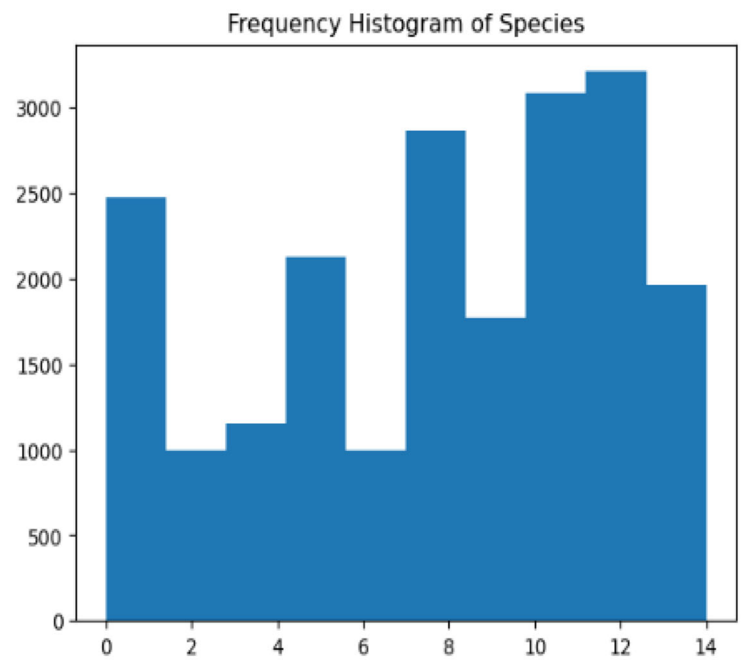


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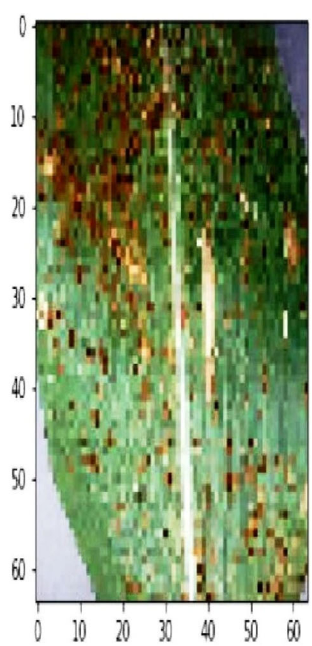
Figure 8. Frequency histogram related to species.



Prediction: disease :- Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot and the pesticide is :-[azoxystrobin, pyraclostro
bin, tebuconazole]

Figure 9. Detecting Corn Cercospora and pesticides to be used.

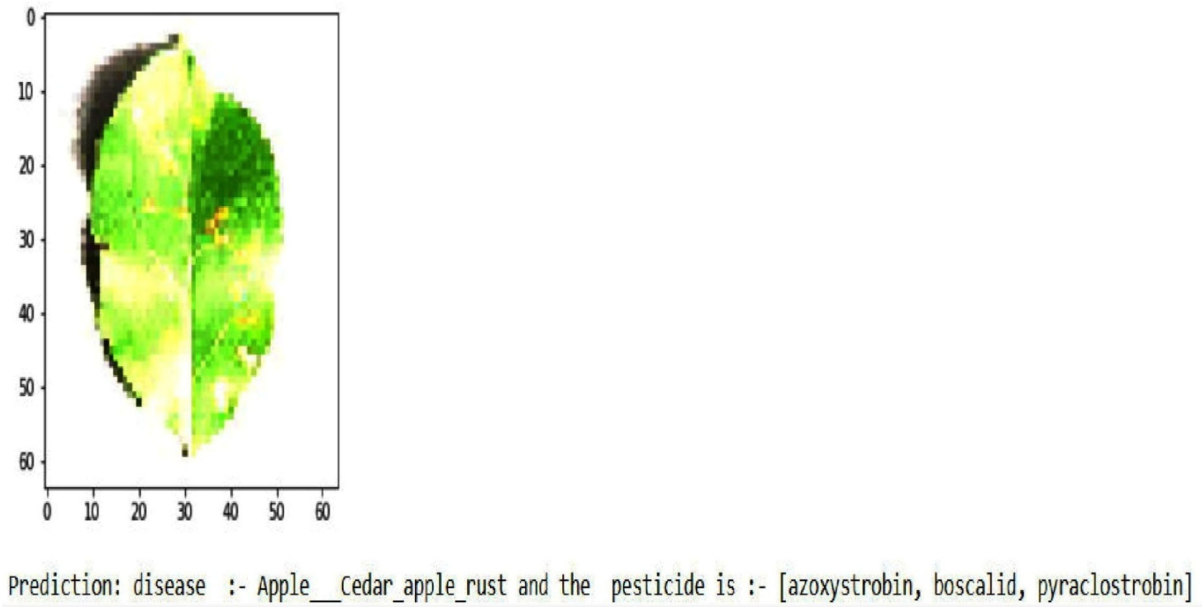


Figure 10. Detecting apple cedar rust bacterial spots.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

- True positive: It is value of positive instances which are accurately identified.
- False positive: This refers to the count of positive cases that have been misidentified.
- True negative: It means the count of not positive cases that are correctly identified.
- False negative: This means value of not positive cases which have been identified incorrectly.

Recall:

It is a measure of the method's ability to identify all positive cases.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

Specificity:

Specificity is the percent right labeled offset cases to the all count negative notes.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

F1-Score: It is a measure that determines accuracy of detection.

$$\text{F1-score} = \frac{2 * Recall * Precision}{Recall + Precision} \tag{5}$$

As shown in Figure 7, the customized Corner Net model's improved recall factor, which enables it to reliably differentiate each category, gives it the ability to detect every classification of leaf diseases. A confusion matrix was generated for various types of leaf diseases in plants. The matrix illustrates the accurate and predicted grades identified by the model.

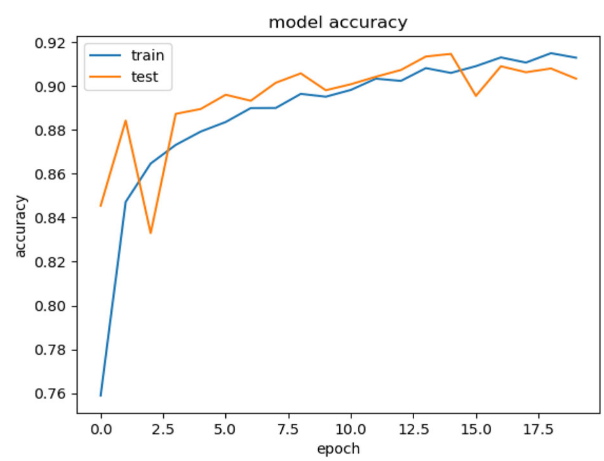


Figure 11. Graph of accuracy.

5. Results

5.1. Visualization for data distribution

This section presents the results of proposed system. Figure 8 shows the frequency of disease types of plants represented using histogram.

5.2. Disease prediction and pesticides recommendation

Figure 9 shows the diseases identified on corn maize leaf and the recommended pesticides to recover

Figure 12. Graph for loss.

from disease. Figure 10 shows the disease identified on apple leaf and recommended pesticides for recovering the apple plant from that disease.

5.3. Accuracy score of model

The model comprises 121 layers, consisting of four thick blocks, each separated by a transition layer. Figure 11 (Simonyan & Zisserman, 2014; He, 2016) illustrates the training and validation accuracy/loss graphs plotted over a period of 30 epochs. Upon testing the model after completion of training, it was able to achieve a maximum accuracy of 92%, with a calculated maximum validation loss of 28% (Figure 12).

6. Conclusion and future scope

Our work comprised a thorough examination of transfer learning models that could accurately classify 15 different herb infections. By utilizing transfer learning methods, we standardized and evaluated sophisticated convolution neural networks based on their precision in classification, sensitivity, specificity and F1 score. According to our investigation, DenseNet-121 performed superiorly compared to ResNet-50, VGG-16 and Inception V4. Due to its simpler computational complexity and fewer trainable parameters, the DenseNet-121 model was simple to train. Therefore, when incorporating a new plant disease into the model, DenseNet-121 is highly appropriate to detect plant diseases, as it requires less preparation complexity. Our introduced method accomplished an impressive accuracy for classification of 92.81%

Disclosure statement

There is no conflict of interest with anyone for this work. There are no relevant financial or non-financial competing interests to report.

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About the authors

Dr. Srinu Banothu and Dr. Karanam Madhavi are involved in conceptualization, methodology and coding and both are also very much inclined for interdisciplinary works.

Dr. K. M. V. Madan Kumar is involved in machine learning model designing, data set gathering and analysis.

Dr. G. Ramesh and Dr. Ch. Mallikarjuna Rao are supported in results validation, formal analysis and investigation.

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Data availability statement

The authors are willing to share the experiment data to the interested researchers on request to the corresponding author.

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