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# Leaf Diseases Prediction Pest Detection and Pesticides Recommendation using Deep Learning Techniques

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***Abstract*— Problems with crop production and plants are common in India, affecting rural farmers, the agriculture industry, and the economy as a whole. Leaf plays a significant role in Plants and Crops because, depending on its condition, it provides information in advance about the quantity and quality of agricultural yield. This study has proposed a Deep Neural Network (DNN) algorithm based disease classification, pesticide recommendation and pre-processing of leaf images obtained from a plant village dataset. After expanding the plant leaf image's data set through geometric manipulation, the extended dataset is separated into a train dataset and a test dataset. After that, the large ImageNet image data set is used to train the ResNet-50 models. In this study, the pre-learned data model constraints are conveyed to the lesser model image dataset of plant infections to train the leaf diseases, pest recognition, and pesticides recommendation model founded on the concept of transfer learning. On a number of diseased leaves, this method is tested. The results of experiments demonstrate that using the transfer learning-based CNN method will improve the higher accuracy and performance efficiency for plant sprig image detection. It is capable of rapidly and precisely diagnosing crop diseases, reducing pesticide and fertilizer use, and increasing crop yield and quality.**

**Keywords— Deep Learning, Machine Learning, RESNET-50, Pest Detection, Recommendation**

## I. INTRODUCTION

Pest management is necessary to increase agricultural productivity and food quality while decreasing expenses and raising revenues, which have lately become important. Insect pests are among the most frequent sources of agricultural harm globally. If these losses are decreased, a substantial amount of the produce might be preserved, and agricultural profitability could increase.[21-23] Harvest damage and disease outbreaks brought on by pest infestations result in lower yields. Insect damage in the areas where wheat, rice and soy beans are harvested is one of the main aims for output losses. To decrease insect populations and stop their spread across wide regions, pesticides and additional bio controller methods must be utilised. Pest control involves the use of a lot of chemicals and insecticides.[19]

They motivation, though, have a variety of harmful repercussions on both humanoid fitness and the background.[18] By way of an outcome, farming experts from around the world started working together to develop superior chemical pesticide substitutes for pest management.[42] The sector's overall economic growth would benefit from addressing and reducing these problems in order to produce a significant volume of nutrition through fewer normal resources.

Additionally, it is essential to identify the insect because pest management methods vary by species.[45] The first stage in averting crop impairment produced by bug vermin is the ability to recognize and categorize insects, distinguishing between healthy and harmful varieties. However, it is difficult to classify insects because of the similarities between different species and their intricate anatomy.[31-33] Most of the time, entomologists must categorize pests by big hand, which takes a lot of time, is hard, and requires a deep understanding. Involuntary pest organization has increased admiration in current centuries due to the ongoing and costly supervision required for this activity. Experts have also utilized a variety of computer-aided categorization methods to resolve these issues. Based on machine learning (ML) techniques, numerous high-tech pest taxonomy approaches have in recent times been obtainable[36]. While traditional ML algorithms may work effectively when there are only a few crop pest species, they can face limitations as the number of landscapes to be covered increases. They require a crucial additional equal of information pre-processing recognized as feature manufacturing[40]. Additionally, it lacks the ability to generalize across datasets. Additionally, their effectiveness is contingent on the data that is available; For instance, a small dataset has a negative effect on accurateness, then once a convinced level of correctness has been reached, growing the data-set has slight impact on enactment.[28] When it comes to the classification of insects, the same challenges are faced.

The study's motivation stems from the fact that, despite the numerous studies on pest recognition and classification, automated systems with high accuracy are still in demand. Although there have been a rare recent educations on pest classification and recognition, this area of research remains understudied.[37-39] In current research, the most prevalent pest classification and recognition method is transfer deep learning (TL) of pretrained DL backgrounds. [27]

## II. RELATED WORKS

According to P. Mäder and J. Wäldchen, et al. [1], plant species can be identified using a manual procedure by using identification keys that are assessed sequentially and adaptively. To narrow down the number of potential species, the user of an identification key answers a series of questions related to various properties of the unknown plant, such as its color, form, number of petals, or presence of thorns or hairs. The desired species is eventually reached through this series of questions answered. However, the majority of nature enthusiasts are unable to perform this task because it requires a significant amount of botanical knowledge to identify plant species from field observation. The identification of traditional plant species is difficult even for professionals who deal with vegetal subjects on a everyday base, such as environmentalists, foresters, farmers and landscape designers. The general public finds it almost impossible to identify these species. Identifying a species can often be difficult, even for botanists. The growing lack of qualified taxonomists exacerbates the situation further. The limited number of taxonomists and the high biodiversity that is still present but is rapidly declining present significant obstacles to the advancement of biological research and conservation in the future. analyzing digital images and recognizing patterns have recently been developed by taxonomists as more effective approaches to species identification.

S. H. Lee and others [ 2], DL is a class of machine learning methods with various dispensation layers that allow for several degrees of data abstraction learning. An introduction to deep learning opens this paper. The framework of herbal detection, i.e., the method by which botanists use morphology to delineate species, is then discussed in depth and critical detail. Then, in this work, we learn and identify important characteristics for leaf data present the concept for autonomous processing and categorization using DL. We explain how visual attention can be used to adapt and learn computational methods. This passage discusses the prevalence of variability in natural objects, including species, and how it can complicate the task of categorization. The passage also suggests that variations in natural objects can potentially be used to improve deep learning solutions. Many studies in the field of plant identification have focused on utilizing leaf databases, but it is widely recognized that leaf features can vary depending on the data and feature methods used. There has been ongoing ambiguity regarding the optimal set of structures to represent a leaf.

The preservation of biodiversity and the sustainable growth of agriculture both need correct information of the identification, topographical delivery, and usage of plants, according to the author Jolly [3]. The fact that recognizing plant species is often hard for the general public, complex for specialists like farmers and forestry workers, and even difficult for botanists themselves, plainly causes and exacerbates the taxonomic gap. Accelerating the collecting and A crucial stage is the incorporation of unprocessed botanical observation facts toward the sustainable growth of agriculture and the preservation of biodiversity. The fundamental contribution of this study, which was developed within the context of a citizen science initiative, is a novel collaborative process focusing on identification as a method to engage new participants and ease entrance to data. In 2010, tens of thousands of geotagged and timed plant photos have been gathered and revised from a specialized social network. Thanks to an image-based identification tool that is synced with the growing data and is accessible as a web and mobile application, any user may query the system or enhance it with fresh observations. This approach is a huge advancement over earlier ones that mainly used the leaf. It can function with up to five distinct organs. This enables the system to be queried at any time of the year with complementing photos that make up a plant observation.

N. Boujemaa, el.at., A. R. Sfar [4], a paper focused on fine-grained categorization, the process of identifying species from images by distinguishing between subcategories of a fundamental group like an object shape and class. While basic categories like trees, dogs, and so on can typically be used to quickly identify instances, Fine-grained categories like plant species and dog breeds are typically only recognized by experts. The difficulty arises from the fact that taxonomic categories frequently have minute differences that remain difficult aimed at the common sense to notice. In other areas of acceptable grained categorization, the situation generally same, which increases the enquiry of how much semi mechanization, is necessary to produce valuable consequences. In order to accomplish, enlist the help of the user per the intention of attaining reasonable in amid the dual excesses of a very accurate completely manual detection and an inaccurate but completely automated detection.

R. Parekh, J. Chaki at. [5], plants are essential to Earth's ecology because they provide food, shelter, and a healthy atmosphere that can be breathed in. In addition, plants are utilized for alternative energy sources like biofuel and have important medicinal properties. A crucial a measure for their protection and conservation is the creation of a database of plants for rapid and accurate categorization and identification. This is especially significant because frequent deforestation to make way for modernization is threatening to wipe out numerous plant species. Digital plant cataloging systems have recently been prepared using computer vision and pattern recognition methods to efficiently identify plant species. Taking this point of view into consideration, the current work makes a novel plan for a plant recognition system that is based on digital images of plant leaves. The shape and texture of the leaf, two prominent characteristics of a particular plant type, help people identify it. A set of computer-identifiable features was used to represent these characteristics using data modeling techniques in this study. Curvelet transform Gray Level Co-occurrence Matrices provide the basis for the Gabor filter's outputs and metrics. used to model the texture. After that, the features are divided into an amount of pre-defined classes by two neural-based classifiers.

N. Kumar, P. N. Belhumeur, [6] was created to significantly expedite the manual process of identifying, accumulating, and keeping track of plant species. Manual navigation of a dichotomous key (decision tree) is required. in order to search the taxonomic tree's numerous branches and seemingly endless nodes without visual recognition tools like Leaf snap. Experts find this challenging, while novices find it exceedingly challenging—if not impossible. Initial attempts by untrained users to photograph leaves in situ result in images that we are unable to process (typically as a result of segmentation failures) due to the presence of multiple leaves among the clutter, severe lighting, and blurry artifacts. Additionally, a lot of users take pictures of things other than leaves. a binary leaf-versus-non-leaf classifier is first applied to all input images to address these two issues. We let the user know this and show them how to take a suitable picture in the event that this classifier determines that a single leaf placed on a light backdrop in the input image devoid of texture and other clutter is invalid.

P. N. Belhumeur [7] and N. Kumar at., Ayurveda is a traditional system of herbal medicine that emphasizes plant-based ingredients in addition to minerals and some animal products. It primarily focuses on disease and illness prevention. This fundamentally founded on pictures, contain the plant and different pieces of the florae, for example, organic products, blossoms, and dust grains and so on. As a result, an enormous amount of digital data accumulates, necessitating classification and retrieval. It is critical to have a computer vision system that uses digital databases to identify plant species in order to provide laypeople with information about medicinal plants. A symbolic method for classifying plant leaves according to their texture characteristics is proposed in this work. The use of MLBP to extract texture characteristics from herbal leaves is proposed. The maturity levels, acquisition, and environmental conditions of a plant can influence the texture of its leaves, even when they belong to the same species. As a result, the idea of grouping is used to select manifold class agents, and interval valued type symbolic features are used to record intra-cluster variations. A straightforward nearest neighbor classifier aids in classification.

L. C. Uzal, G. L. Grinblat, et al., [ 8], Deep learning algorithms are increasingly taking the place of traditional methods in many common machine vision applications. The advantages are worthwhile: It eliminates the need for specialized, handcrafted features extractors while also ensuring that results are not damaged and frequently improve. For the problem of identifying plants based on patterns in their leaf veins, we propose employing a deep convolutional neural network (CNN). We specifically consider classifying three distinct species of legumes: soybean, red bean, and white bean. As opposed to the cutting-edge pipeline, CNN avoids using handcrafted feature extractors. Furthermore, the accuracy of the referred pipeline is significantly enhanced by this deep learning strategy. Additionally, we demonstrate that increasing the depth of the model results in this accuracy. Finally, we are able to determine which vein patterns are relevant by analyzing the models produced using a straightforward visualization approach. Utilizing a deep learning strategy may be beneficial for addressing a number of agricultural issues that are currently being addressed by conventional computer vision methods.

We use the well-known and tried Bag of Visual Words model in this study to identify plant species from leaf photos, as described by Z. Wang et al. and J. Charters et. [9]. In order to utilize the venation structure and define leaf edge patterns in a spatial context, we offer the innovative EAGLE descriptor. When combined with SURF, our descriptors can more accurately identify species by defining the regional gradient and venation patterns produced by adjacent edges (Speeded-Up Robust Features). The initial stage in the calculation process, edge detection on the original picture, reveals the venation structure. Based on its stated speed and output quality, we employed Canny's edge detection technique in combination with morphological dilation to generate a high-quality binary edge images. Due to the fact that EAGLE uses a patch-based technique for sampling image data, there are two common approaches to collect samples. Using a sliding window over a fixed window, dense sampling involves computing features. A voting histogram is used to visualize the distribution of the order of variation between two Hough lines after the angular differences for the vector of Hough lines have been determined.

R. Namas and M. G. Larese, et al. In the most recent body of research, numerous researchers have addressed the issue of automatic leaf image analysis for the purpose of plant classification or image retrieval. Several approaches have been put forth, such as leaf shape, variety information, and leaf surface analysis. In this paper, a strategy for dividing and characterizing checked vegetable leaves dependent just upon the examination of their veins is proposed (leaf shape, size, surface and variety are discarded).Three vegetable species are contemplated, to be specific soybean, red and white beans. The leaf photos are obtained with a typical scanner. The segmentation is carried out using the unconstrained hit-or-miss transform and adaptive thresholding. Four different classifiers are used to compute and categories a variety of morphological characteristics on the segmented venation: random forests, penalized discriminant analysis, support vector machines (linear and Gaussian kernels), and others. The performance is contrasted with crisp leaf photos, whose capture is more difficult, expensive, and time-consuming.

### A. *Limitation of existing paper*

- Irrelevant features are extracted at the time of leaf classification
- Only consider the shape features of data
- The error rate is high at the time of recognition
- Single categorization can be occurred in plant species
- Not support in real time leaf datasets

## III. Proposed System

Our understanding of plants, which were formerly our closest surroundings and are now more urbanised and artificial, has all but vanished, save for a few professionals.[46-48] In the confusion of what is believed to be irrefutable development, a significant deal of plants, flowers, and trees also had their names and uses forgotten. On the other side, the desire to reconnect with nature seems to be growing in popularity in today's society, along with a certain rebirth of the notion that plant diversity and resources should be respected.[29]

Additionally, letting anybody who feels the need to learn about the past and characteristics of a plant species serves as a way to transmit lost information and a window into nature's incalculable richness. Species identification is the first and most crucial step in comprehending the plant habitat. Botanists have traditionally employed fruit, flower, and leaf appearance and composition to identify species.[11-13] However, in the context of a large non-specialist application, the most logical and popular technique in image processing is the predominance of leaves, which are available virtually all year, are easy to capture on camera, and are simpler to analyse from two-dimensional images. A challenging and important issue arises when attempting to identify a tree from photographs of leaves against a natural backdrop.[26] In this study, we describe a method for addressing the difficulties given by such complicated pictures for simple and lobed tree leaves. The generation of an active contour is later guided by the results of the initial segmentation stage, which is based on a light polygonal leaf model.[] Using a combination of local curvature-based characteristics and global form descriptors supplied by the polygonal model, the leaves are then categorised across leaf datasets. We describe a method for addressing the difficulties provided by such complex pictures in this research for basic and lobed tree leaves.[40] In order to influence the formation of leaf borders, a graph cut-based segmentation stage is first completed.

### *A. Block Diagram*

The diagram can be divided into two phases, such as the training phase and the testing phase, with this architecture. During the training phase, the user uploads a leaf dataset and also performs image noise removal pre-processing. The segmentation algorithm should then be used to group the leaf and label the diseases. During the testing phase, the user enters the leaf and more accurately classifies the diseases.

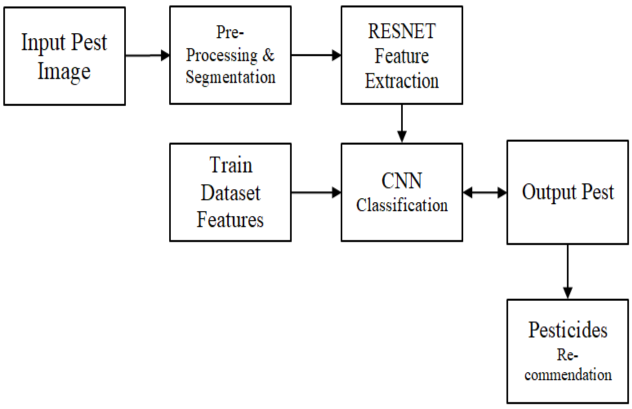


Fig. 1 Proposed Block Diagram

### *B. Proposed CNN Architecture*

A generator and a discriminator make up the proposed RESNET. Figure 1 depicts our RESNET's generator network; The generator network received low-resolution images and split them into two branches. After the generator network's first convolution layer, one went into the upscale module, and then this branch went through the self-attention module.

The other was put into the reconstruction net to anticipate the details after passing through the PReLU activation layer and the second convolution layer. To distinguish between actual high-resolution (HR)images and produced super-resolution (SR) images, the reconstruction net integrated the upscale images and edges with the anticipated information prior to a convolution layer to produce the high-resolution images. Here, max-pooling across the network is avoided by using Leaky ReLU activation.[34-36]

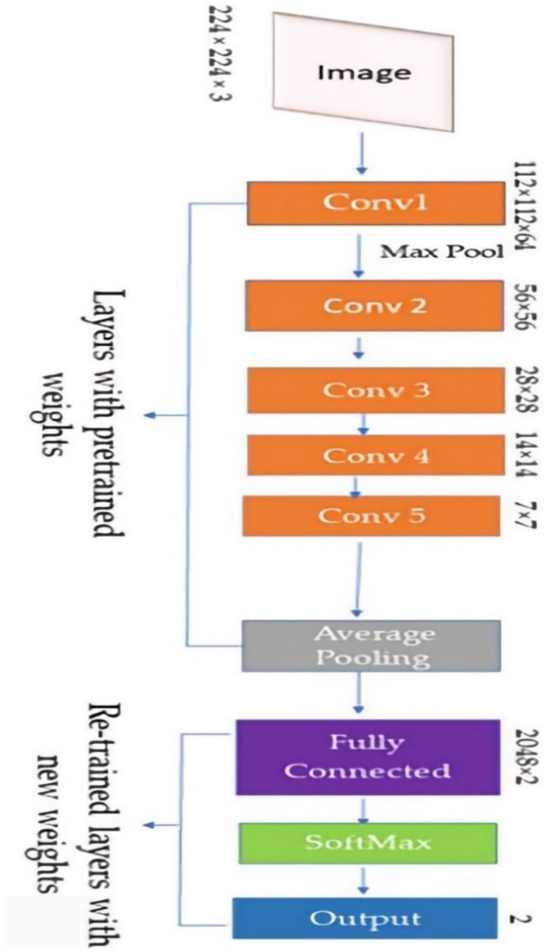


Fig. 2 The customized architecture deployed in the proposed RESNET [48]

The discriminator network is taught the maximising issue. It features seven convolutional layers and a doubling increase in the quantity of filter kernels after 64x64 to 512x512.[20] Static complications are used to decrease the image determination once the amount of features doubles. After producing 512 feature maps, the probability of sample classification is calculated using a final ReLu activation function and two linear layers.

### *A. Data Augumentation*

A challenge when using deep learning approaches for pest recognition and classification is the limited availability of data to train the frameworks. Acquiring a larger quantity of crop pest data is challenging and can be costly in terms of time and resources. However, data augmentation techniques can help overcome this limitation by applying various processes to existing data to increase the amount of available data, which has been proven to be beneficial in image classification tasks.


Fig. 3 The Deng et al. dataset includes sample images of various pests, as shown in the following examples: (a) Locusta migratoria, (b) Parasa lepida, (c) Gypsy moth larva, (d) Empoasca flavescens, (e) Spodoptera exigua, (f) Chrysochus chinensis, (g) Laspeyresia pomonella larva, (h) Spodoptera exigua larva, (i) Atractomorpha sinensis, and (j) Laspeyresia pomonella

### B. *Image Resizing*

To ensure consistency and expedite processing, we implemented pre-processing techniques to resize the input images in the datasets to 224 x 224 pixels. This was done because our model has specific requirements for input image size, and the original images in the datasets were of varying sizes.

### C. *Dataset Partioning*

In each experiment, the dataset was divided into training and testing sets, with 90% of the data used for model training and the remaining 10% used for testing purposes.

### D. *DeepPestNet Architecture Details*

The DeepPestNet DL model was presented in this paper as a solution for pest recognition and classification. It differs from standard CNNs in that it has eleven learnable layers, consisting of eight convolution layers and three FC layers, resulting in a total of thirty-three layers, including various layers such as LR, BN, cross channel normalization, dropout, average pooling, softmax, and classification layers. The input layer of the proposed model is able to process 224 × 224 crop pest images. The initial convolution layer uses 64 kernels of size 7 × 7 with a stride of 2×2 to generate the feature map, which helps extract patterns from the image by breaking it down into smaller parts.

### E. *Hyper Parameter*

DL frameworks' accuracy heavily relies on the choice of hyper-parameters, which are usually determined through a trial-and-error method. The selection of these parameters plays a crucial role in dictating the algorithm's behavior. In order to determine the best value for each hyper-parameter, we tested various values for each one, taking into account the extensive range of options available. Our DeepPestNet model was trained utilizing stochastic gradient descent (SGD), with 80 epochs being used for pest identification and classification, while also considering the possibility of overfitting.[30]

## IV. EXPERIMENTAL DESIGN

We utilised the dataset provided in R. Yu's Research on insect pest picture identification and recognition based on bio-inspired techniques to evaluate the effectiveness of the proposed Pest Detection framework.[17] It consists of ten distinct pest groups, the majority of which are found in tea plants as well as other plants throughout Central Asia and Europe. Pests including Euproctis pseudoconspersa Strand, Locusta migratoria, Empoasca flavescens, Chrysochus Chinensis, and others are depicted in the 10 images in the collection.The proposed method is evaluated using the following evaluation tools: Specificity, F1_score, sensitivity (Recall), accuracy, and precision Equation, which is well-defined as the no of acceptably, noticed or categorized images, indicates the framework's accuracy.[24] F1_score, on the other hand, computes the weighted average of precision and recall by combining the two. These metrics can be estimated using these equations:

Precision = TruePositives / (TruePositives + FalsePositives)

Accuracy = (TruePositives + TrueNegatives) / TotalSamples

Specificity = TrueNegatives / (TrueNegatives + FalsePositives)

Recall = TruePositives / (TruePositives + FalseNegatives)

$$\text{F-Measure} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

TABLE I. FALSE REJECTION RATE OF DIFFERENT ALGORITHM

| Algorithms | FRR |
|---|---|
| Random Forest | 0.42 |
| Adaboost Classifier | 0.35 |
| Support Vector Machine | 0.28 |
| Artificial neural network | 0.20 |
| Convolutional Neural Network | 0.14 |

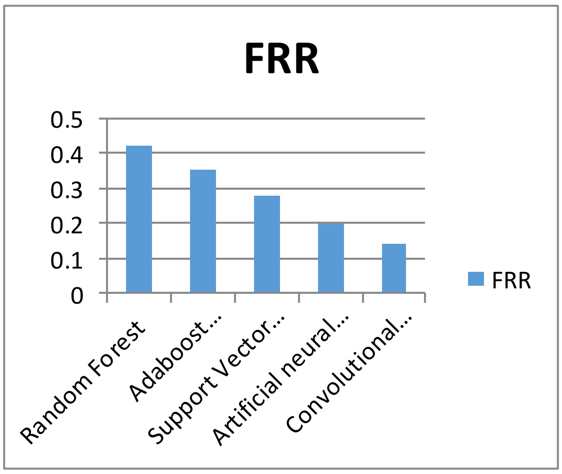


Fig. 3. False Rejection Rate

From this figure 3, The proposed system provides less number of false rejection rate than the existing algorithms:

### A. Performance Evaluation

The aim of this study was to assess the efficacy and practicality of the pest recognition and classification method suggested. In this experiment, all 1686 crop pest images from Deng et al.'s (2018) dataset were utilized, with 1518 images reserved for training the model and the remaining 168 images used to test the model (after rotating the initial images). The proposed framework required 536 minutes and 46 seconds to complete the pest classification training with DeepPestNet, which comprised 1100 iterations during the training phase (11 iterations per epoch) and 100 epochs. To evaluate the proposed method's classification performance in terms of real and predicted categories, a confusion matrix was generated.

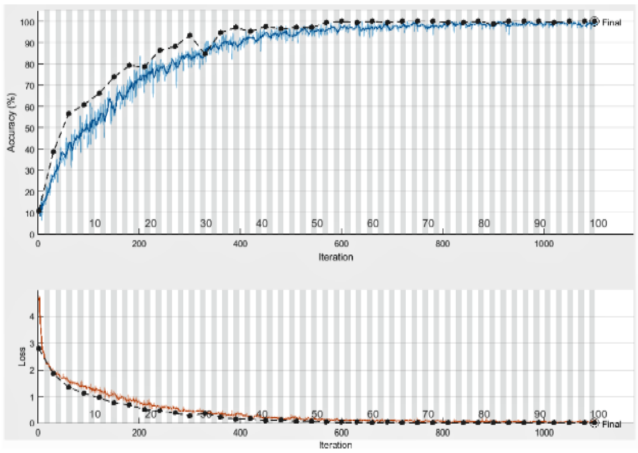


Fig. 4 Training accuracy and loss of PestDetNet model

Fig. 4 displays the accuracy and loss of the presented method during training, indicating that after epoch '55', the accuracy and loss remained consistent, hovering around 100%, implying that satisfactory results can be obtained even with fewer classification epochs. The PestDetNet method was able to achieve a perfect accuracy, precision, recall, specificity, and F1-score of 100% in the classification of pest images, demonstrating its effectiveness for multiclass classification purposes.

The excellent classification accuracy of the model can be attributed to its utilization of convolutional layers that incorporate kernels of different sizes (7 x 7, 3 x 3, 1 x 1). This approach enables the network to learn spatial patterns at various scales and recognize distinctive characteristics. The 1 x 1 filters are effective in identifying patterns throughout the depth of the input pest images, whereas the 3 x 3 and 7 x 7 filters are capable of learning spatial patterns across the input's three dimensions (width, depth, and height). As a result, the use of convolutional filters of different sizes allows the model to learn various spatial patterns and extract unique features from pest images with greater accuracy at different scales.

## V. CONCLUSION

This study provides an overview of the various classification and segmentation methods that have been proposed to enhance the quality of segmentation. However, the outcome demonstrates that the proposed graph cut model cannot be implemented in large datasets and that segmentation algorithms fail to function properly the study has discussed a method for accurately active contour segmenting leaves in natural scenes utilizing the optimization of a polygonal leaf model as a shape prior. Furthermore, it provides a collection of worldwide geometric characteristics that, in conjunction with local characteristics derived from the curvature of the ultimate contour, facilitate the identification of tree species. A segmentation process is carried out based on a color model that can handle unpredictable lighting conditions. However, in the case of leaves that cannot be easily distinguished by color, relying solely on a global color model for the entire image may not be enough. To improve accuracy, it may be beneficial to include a second texture model or an adaptable color model. Last but not least, identify leaf illnesses as caused by bacteria, viruses, or fungus using a neural network classification technique. After that, suggest fertilizers to the afflicted leaves utilizing measurements.

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