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An Accurate Mango Pest Identification Employing the Gaussian Mixture Model and Expectation-Maximization (EM) Algorithm

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Abstract: Mangoes are fruits that originated in South and Southeast Asia. Mango fruits are consumed in high volume worldwide. However, fruit, stem, root, and mango leaves are damaged by pests, and it has a significant negative impact on mango production. Many works were developed for the pest detection of mango; but, none of the works concentrated on the practical applicability and learning efficiency of the model. Furthermore, the boundary features of the leaf regions were not analyzed in depth for accurate identification of different mango pests. Therefore, in this study, Machine Learning (ML) algorithms are used to assess mango fields and identify pests to address the requirement for an early-stage pest identification system. This study presents a novel method for mango plant disease and pest identification and classification using a combination of machine learning, IoT, computer vision, and drone technology. The proposed system is designed to analyze large mango fields and detect biological threats in an early stage and the problems faced by farmers in mango crops. The system utilizes a Dense Net architecture for feature extraction and a custom Corner Net model employing the Gaussian Mixture Model and Expectation Maximization (GMM-EM) algorithm for effective pest classification. The proposed system is tested using the IP102 dataset, which is a large challenging benchmark database for pest identification. The experimental results represented the enhanced pest detection of mango crops with an accuracy of 89.90%, precision of 79.94%, recall of 75.82%, and F1-score of 77.80% by using the proposed model. Furthermore, the proposed system is robust and can reliably locate and categorize different pests even in complicated backgrounds and various insects and their color, size, and brightness. The proposed approach can also send SMS notifications to farmers concerning diseases and pests.

Keywords: Mango, Leaf Disease, Pest Identification, Pest Classification, Machine Learning

Introduction

The agricultural industry, more specifically the farming community, has struggled with pests and environmental disturbances for a very long time. It is now widely acknowledged that these issues are serious concern to both economic security and food production as well as the general public (Komarek *et al*., 2020). Farmers have traditionally dealt with these issues using their local expertise, which has been handed down through the generations and opened the path for reducing some of the effects of pests (Kusrini *et al*., 2020). Despite the fact that many industries in the Indonesian region have embraced the use of state-of-the-art scientific tools and solutions, the automation of agricultural services has not yet made use of machine-learning network models that leverage mobile computing and the Internet of Things (Ouhami *et al*., 2021). Among the several agricultural plant species that are damaged, pest infestation of leaves is estimated to have the biggest influence on food production (Malhi *et al*., 2021). According to a report by Statista 2022, Indonesia produced 2.86 million metric tonnes of mangoes in 2021 (Mona, 2023). To maintain production, it is necessary to ensure that the diseases affecting the quality of food production can be minimized (Kusrini *et al*., 2020). To address this serious agricultural issue, farmers are now required to physically inspect and track the frequency of leaf infestation (Raj *et al*., 2021). The expansion of mango plantation areas within Indonesia makes it impractical for farmers to perform extensive inspections of mango farms (Lalitha, 2020).

Today, Integrated Pest Management (IPM) systems and solutions are being automated. So, researchers are putting more effort into developing cutting-edge technologies and methods for this purpose as a result of technological growth in the Internet of Things (IoT) and smart handheld device industries (Suma, 2021). IPM seeks to create and implement a pest management plan for agricultural output that employs a variety of strategies and takes into account the effects on the economy, environment, ecology, and public health (Deguine *et al*., 2021). If farmers are going to fully adopt the use of such IPM systems, then quick and accurate processing of reliable data from wide agricultural fields is important (Muriithi *et al*., 2021). Farmers must deal with a number of difficult issues, such as the weather and agricultural pests, in order to take care of their crops and increase production (Roslim *et al*., 2021). In traditional agricultural pest identification, crop pests are categorized by placing real insect traps for inspection. However, these techniques lack accuracy and often have large error rates (Hang *et al*., 2019).

Furthermore, a lack of readily available agronomists may sometimes cause delays in the process of pest identification. It is also difficult to choose the proper insecticide kinds, which leads to the blind application of pesticides (Iost Filho *et al*., 2022). This is due to a lack of distinct pests and the visual analysis between different insects. The quality and quantity of crops might suffer if farmers are unable to act swiftly owing to the delay in insect identification. However, it requires time and effort to determine the kind and number of agricultural pests (Orchi *et al*., 2021). Early pest detection and timely pesticide application to the plants may contribute to economic growth.

According to recent developments in Machine Learning (ML), Computer Vision (CV), and the Internet of Things, an automated method should be offered to speed up this process and develop effective insect identification systems. Traditional ML-based methods are initially used to develop classifiers like SVM (Saleem *et al*., 2021a) and Local Binary Pattern (LBP) using local descriptors (Thangaraj *et al*., 2022), Local Ternary Pattern (LTP) (Vishnoi *et al*., 2022), SIFT and SURF (Domingues *et al*., 2022). Numerous studies have been conducted on these methods for the classification of pests (Aziz *et al*., 2019; Aurangzeb *et al*., 2020; Phung and Rhee, 2019). Less training data is required for a hand-crafted computing approach, but it requires the expertise of qualified human professionals. Additionally, these difficult datasets are a consequence of recent improvements in picture capturing. Conventional techniques, such as machine learning, perform substantially poorer when it comes to categorizing objects and have little potential for identifying pests in the real world. Numerous reasons, such as inaccurately calculated hand-crafted key points, may be to blame for this (Carboni *et al*., 2020). The same bug may appear in several photographs in a variety of motions and locations, which leads to the production of unique key point vectors for the same pests (Evans *et al*., 2020). The improvement of the detection effectiveness for a certain pest category is the main objective of the research community when introducing new key point solutions. Such studies do not focus on creating new frameworks for multi-category pest detection missions that call for the gathering of information on insect localization and classification to support pest monitoring. This study offers the IP102 benchmark dataset with real-world pests collected due to the many difficulties encountered by Indonesian farmers while growing mangoes. By using drone-captured images of mango agricultural regions, a unique Gaussian mixture machine learning network is then developed to offer a baseline for the categorization of six distinct types of pests on six sick mango leaves. The paper also outlines a comprehensive, all-inclusive methodology that farmers may use to identify pests in their farms. Also, a farmer receives an SMS, which alerts them about the disease and pest.

Literature Review

Singh *et al*. (2019) created a multilayered CNN for categorizing mango leaves affected by the fungus anthracnose. To test the model, the researchers used 1070 photographs of a real-time dataset of mango leaves obtained in Jammu and Kashmir. The set included both healthy and sick leaves. The results proved that the MCNN model surpassed other techniques in terms of classification accuracy.

A complete paradigm for classifying illnesses that harm mango leaves was developed by Prabu and Chelliah (2022). The images were taken from India's largest mango orchards. The framework comprised four stages: Choosing features, learning and classifying, assessing performance, and gathering data. 380 pictures of plants in good health and inflicted with disease were chosen (Sooty mold, Bacterial black spot, and Mango Anthracnose). To reduce overfitting and increase generalization, different data augmentation techniques were used. Then, for more effective feature selection, a CNN was used. The trained version was also utilized in the learning stage of the SVM, and the Mobile NetV2 model was used in the analysis stage to classify the illnesses that affected leaves. The trial's outcomes showed that the categorization performances outperformed those of other techniques.

A method was created by Aurangzeb *et al*. (2020) for the automated detection of potato and maize leaf diseases. Some of the manually created elements that were taken from the three basic design processes included Local Ternary Patterns (LTP), Segmented Fractal Texture Analysis (SFTA), and Histogram-Oriented Gradient (HOG). To end the dimensionality curse, the second step employed Principal Component Analysis (PCA) and entropy-based score values. Data classification using a variety of classifiers was the last phase. By utilizing information from Plant Village, certain diseases in potatoes and maize were identified and categorized. When compared to the presented methods, competent outcomes on a variety of agricultural illnesses were obtained in the range of 92.8-98.7%.

An explanation of the strategy recommended by the research articles was given by Raina and Gupta (2021). The images were examined by many researchers using artificial intelligence, showcasing their successes and recurrent issues. The article included datasets that were freely accessible and a summary of the existing methods for addressing the issue at hand.

In order to distinguish the sick region, (Saleem *et al*., 2021b) used a unique segmentation method that considered the leaf pattern. The leaf vein-seg approach was applied by dividing the leaf. Then, using Canonical Correlation Analysis (CCA), feature extraction and fusion were performed. To confirm the findings, a cubic support vector machine was used.

Using historical meteorological data and agricultural productivity, (Jawade *et al*., 2020) predicted the disease assault on the mango fruit crop. Weather sensors in the field gathered information to detect infections. The chance of a disease breakout could be predicted using the Random Forest Regression model, which was trained using weather data. The model's predictions for illness were surprisingly accurate.

Iniyan *et al*. (2020) research employed ANN and SVM techniques to identify agricultural illnesses. They evaluated each approach's benefits and drawbacks in light of the input parameters as the last step in their investigation (Crop type). Arivazhagan and Ligi (2018) implemented a deep-learning model to identify leaf ailments in several mango plants. The authors used a mango leaf dataset consisting of 1200 images, which was feasible for recognizing five common leaf diseases.

A modified version of the VGG Net model developed by Venkatesh *et al*. (2020), called V2IncepNet, combined the VGG Net and Inception modules. The VGG Net was used to retrieve fundamental qualities, while the Inception module gathered high-dimensional features and categorized images. They assessed the following traits: The color of the leaf, its venation, the condition of the petiole, the form and condition of the tips, the shape of the leaf, the leaf border, the presence of black spots on the midrib and leaf blade, and the edge of burns on the leaf, leaf blade, and petiole. This data set contained 2268 color photos of mango leaves, including 1070 from Plant Village and 1198 from individual real-time color shots taken in the field. The results obtained from the experiments indicated that the model classified the disease-affected mango leaves.

In order to help mango growers in Pampanga, (Tumang, 2019) used leaf and fruit markings to detect pests and illnesses. This enhanced agricultural management, especially with regard to pesticide use. Here, the pests and farmers' unwillingness to use pesticides for every pest problem were major reasons for the sudden drop in mango production in the Philippines and this fixes that problem. It was found by extracting entropy, skewness, kurtosis, contrast, and kurtosis.

Muthaiah and Chitra (2023) improved mango pest detection based on optimization techniques. Initially, the data was collected from the dataset; then, the features were extracted using the Scale Invariant Feature Transform method. Further, the significant features were chosen by utilizing the Extreme Learning Machine along with the Whale Optimization algorithm. At last, the mango pests were classified using the Support Vector Machine (SVM) model. The experimental results proved that the performance of the model was best in terms of precision, recall, and f-measure. However, the need for selecting an appropriate kernel and vanishing gradient issue in the utilized SVM limited the classification performance.

Rizvee *et al*. (2023) introduced a technique named Leaf Net for classifying multiple diseases of mango leaves. Here, the leaf images were collected from the Bangladesh region. Further, the image features were mapped and subjected to the Leaf Net model. The resultant outcome depicted the enhanced performance of the introduced technique regarding accuracy and computational time. However, the lack of image preprocessing included the imperfect images in data training and restricted the model's interpretability.

Gautam *et al*. (2024) presented the deep learning model for disease detection in mango leaves. At first, the images were gathered and segmentation was done. Then, the segmented image was inputted into the stack of different deep neural networks. Further, the leaf disease was detected by accumulating the outcome of multiple DNNs with the machine learning model. When compared with the conventional methods, the presented model exhibited better performance based on accuracy. However, the adopted ensemble approach increased the complexity and computation time, thus reducing the classification efficiency.

Seetha *et al*. (2023) suggested the disease classification of mango leaves with a hybrid optimization approach. The mango leaf images were taken, and further they were preprocessed to enhance the image quality. Here, the background subtraction and edge detection were carried out. Further, the image was segmented based on the region and the edge. Then, the prominent features were extracted by utilizing Local Binary Pattern (LBP) and Local optimal-oriented pattern methods. Subsequently, the diseases were classified using the Machine Learning-based neural network. Further, the authors used a hybrid Coyote-Grey wolf optimization algorithm to improve the classification accuracy. Thus, the performance was increased regarding accuracy, precision, and recall. Yet, the utilized LBP could not capture the discriminative characters among image data, resulting in unreliable feature extraction.

Rajpoot *et al*. (2022) improved the crop yield by effectively detecting the mango plant disease. Firstly, the image was gathered, and it was flattened and resized based on the threshold value. Further, the foreground and background image pixels were deviated for recognizing patterns by using the Brightness Preserving Bi-Histogram equalization method. Then, the features were extracted, and the diseases were classified using the Convolutional Neural Network. Thus, the mango plant diseases were classified by the presented approach with higher accuracy. Hence, crop production was improved by the accurate detection of disease in advance. However, the various types of pests in the mango plant were not focused on, which restrained the detection reliability.

Bezabh *et al*. (2024) recommended a mango disease classification approach to enhance mango productivity. Initially, the data were collected from the Merawi Agriculture Research Center. Then, the data was preprocessed by resizing and noise removal for effective detection. Further, image segmentation was done by combining k-means and mask Convolutional Neural Network methods. Subsequently, the features were extracted by employing the CNN. Further, the fully connected layers classified the diseases of the mango plants with higher accuracy and precision. Hence, the yield of mango crops was significantly increased with the help of this approach. However, the real-time applicability was not clearly exposed by the model, which remained a questionable part.

Nti *et al*. (2023) introduced the predictive analysis model for the welfare of crop productivity and suitability. Here, the factors for crop growth were obtained from the kaggle source. Then, the outliers were recognized based on the z-score to develop the exact prediction. Then, the productivity of the crop was predicted by using six different tree-structured ensemble models. Further, the output of each model was collectively attained by the stacking of the tree-based ensemble technique. The evaluated results depicted the enhanced prediction of various crop productivity, including mango plants with increased accuracy. Yet, the usage of different models for prediction elapsed the prediction time and complexity.

Literature Summary and Research Novelty

To answer the research question and to fill the gap as discussed in the previous section, the following two hypotheses are proposed.

As discussed earlier, many authors explored various techniques to develop efficient disease identification for mango leaves. In existing (Singh *et al*., 2019; Prabu and Chelliah. 2022; Saleem *et al*., 2021b), the applicability of the model in real-time was ensured. Also, the model was trained with limited data in these prevailing works. Hence, the proposed work gathers images using the drone camera, thus demonstrating the real-time applicability of the work. Further, a large amount of data was utilized from the standard dataset for effective analysis. In most of the related works, including (Raina and Gupta, 2021; Iniyan *et al*., 2020; Tumang, 2019; Muthaiah and Chitra, 2023), the SVM used disease classification. However, this technique was always prone to overfitting issues, which were not intended to be suppressed in these existing works, resulting in poor training and detection. So, the proposed work utilizes the Corner Net-based GMM-EM algorithm to effectively train the data by deeply analyzing the boundary features. Furthermore, the lack of data preprocessing included noisy or imperfect data in the training, which complicated the process and reduced the detection accuracy in Rizvee *et al*. (2023). Hence, the proposed work uses a QDFT-based filter to remove the image noise and improve pest detection.

Table 1: Summary of research gap

References	Techniques	Limitations
Singh *et al*. (2019)	Multi-scale Convolutional Neural Network (MCNN)	Need to build a real-time disease-monitoring system
Prabu and Chelliah (2022)	Convolutional Neural Network (CNN)	Need to increase the number of images in the dataset
Aurangzeb *et al*. (2020)	Local Ternary Patterns (LTP)	Accuracy problem
	Segmented Fractal Texture Analysis (SFTA)	
	Histogram-Oriented Gradient (HOG)	
	Principal Component Analysis (PCA)	

Raina and Gupta (2021)	Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Global Pooling Dilated Convolutional Neural Network (GPDCNN), Generative Adversarial Network (GAN), Support Vector Machine (SVM), Particle Swarm Optimization (PSO)	Overfitting problem
Saleem *et al*. (2021b)	Canonical Correlation Analysis (CCA), cubic Support Vector Machine (SVM)	To (1) increase the images in the dataset (2) To reduce the time using a feature optimization algorithm
Jawade *et al*. (2020)	Random Forest Regression	The model was extended to introduce Mango orchards
Iniyan *et al*. (2020)	Artificial Neural Network (ANN) and Support Vector Machine (SVM)	ANN-based methods are better than SVM
Arivazhagan and Ligi (2018)	Deep Convolutional Neural Network (DCNN)	Finding optimal parameters for a CNN model is still a research challenge
Venkatesh *et al*. (2020)	Visual Geometry Group Network (VGG Net), Inception module induced Visual Geometry Group Network (V2IncepNet)	Expensive and time-consuming
Tumang (2019)	Multi-Support Vector Machine (Multi-SVM) and Grey Level Co-occurrence Matrix (GLCM)	The pests and diseases were explored by RGB values of the leaves and adjusted to the camera used
Muthaiah and Chitra (2023)	Extreme Learning Machine- Whale Optimization algorithm (ELM-WOA), Support Vector Machine (SVM)	The requirement of a suitable kernel and the overfitting issue in SVM lowered the performance
Rizvee *et al*. (2023)	Leaf Net model	Preprocessing of leaf images was not carried out, thus leading to sub-optimal disease classification
Gautam *et al*. (2024)	Stack ensembled Deep Neural Network	Higher computational time and complexity
Seetha *et al*. (2023)	Local Binary Pattern (LBP), Local optimal-oriented pattern, Machine Learning Neural Network, and hybrid Coyote-Grey wolf optimization algorithm	Discriminative characters of the image were not effectively captured for disease classification
Rajpoot *et al*. (2022)	Brightness Preserving Bi-Histogram Equalization and Convolutional Neural Network (CNN)	Different types of pests in the mango plant were not identified
Bezabh *et al*. (2024)	K-means, Mask Convolutional Neural Network (M-CNN), and Fully connected classifier	Real-time applicability of the model was constrained
Nti *et al*. (2023)	Gradient Boosting, Random forest, extreme gradient boosting, Gradient boosting, categorical boosting, and light gradient Boosting machine	Had higher complexity and required more time for crop yield prediction

Moreover, the prevailing works didn't alert the farmers about the pests or diseases to prevent the further spreading of disease among the mango crops. Hence, the proposed work alerts the farmers regarding the identified pests through the SMS and protects the crops from future diseases, thus assisting in increasing the mango crop production. Therefore, the proposed work contributes to producing an efficient disease detection system by tackling the issues in previous works on mango disease identification and classification.

Problem Statement

Pests that severely diminish the mango's fruit production often attack the fruit, stem, and root of the plant. A computer-aided strategy should be offered to speed up this process and develop an efficient automated insect identification method, according to current developments in Machine Learning (ML), Computer Vision (CV), and the Internet of Things. SVM classifiers are employed with local descriptors in ML-based approaches, such as local binary patterns and regional ternary patterns. This method is now extensively examined with the aim of identifying and classifying pests. Additionally, these difficult datasets are a consequence of recent improvements in picture capturing. These traditional methods, which use Machine Learning as a sudden solution, show little promise for locating pests in the real world and perform noticeably worse when categorizing things. This might be caused by different factors, including improperly calculated hand-crafted key points. The same pest may also travel and show up in several photos in various locations, which results in the development of distinct key point vectors for the same insects. To enhance the detection performance for certain bug kinds, the research community's novel key points solutions are mostly focused on this purpose. Such studies do not focus on creating new frameworks for multi-category pest detection missions that require the gathering of information on insect localization and classification to support pest monitoring.

This study presents research that proposes a Machine Learning (ML) technique for identifying pests in mango fields using computer vision. Combined machine learning and IoT techniques are used to identify an early-stage automated pest identification system, thereby resolving numerous issues plaguing mango cultivation among Indonesia's farming community.

Materials and Methods

The study's novel contributions to the pest detection of mango leaves include:

1. A benchmark dataset is created for IP102 using drones to overcome the practical constraints of identifying and classifying six different mango diseases and six different mango pests in mango leaves
2. To create and put into new practices, cutting-edge Gaussian mixture algorithms using machine learning are integrated with the drone-captured images of mango crop fields
3. To accurately identify and classify the pests in mango leaves, the processes, including image pre-processing, feature extraction, and segmentation, are adopted in this proposed work using advanced image-processing techniques
4. For producing the accurate detection of mango pests, the features of leaf images are analyzed through boundary recognition by using the Corner Net model
5. The spreading of pests among the mango leaves is prevented by intimating the farmers about the disease and pest through SMS after detecting the pests

The proposed pest detection approach is based on the examination of actual photographs taken by inexpensive handheld cameras in the mango plantations. One of the crucial criteria that the study addresses is the absence of tools for pre-processing the pictures that farmers take. The analysis of the farm picture as-is has a special set of difficulties due to the background's complexity, other pests' overlapping leaf structures, and partial occlusions. The training of the pest identification framework is done in order to get over these obstacles. The generally recommended architecture is shown in Fig. (1).

Image Acquisition Using Drone "DJI Avata

The image of the ill mango leaf is taken using the drone's digital camera. For best quality, the photo is shot from the "DJI Avata" drone camera at a certain distance (DjiAvata, 2023). In the unlikely occasion that it isn't, the picture is shot at a certain, uniform distance with enough light to identify the subject. The color of the leaves in the photo should be in sharp contrast to the background. According to a comparative study, black background photographs provide better findings in detecting diseases that affect mango leaves. Both a black and a white background are used in the creation of the dataset.

The DJI Avata's f/2.8 aperture &1/1.7-inch CMOS sensor enable it to capture 4K footage at a very wide angle. Along with top-notch imaging performance, it offers stunning visuals that will have the audience on the edge of their seats (4K/60fps using a 1.75 mm sensor 155° Super-Wide FOV Video D-Cinema Mode Horizon Steady EIS) (Kusrini *et al*., 2020).

The detection is done using a drone camera that is 30 cm wide and 35.8 cm long in an open field of mango trees. The drone camera is placed 50 cm above the surface of the plant. On the basis of the gathered day, each trap is recognized and given to a certain group. Mango leaves are photographed using a high-resolution drone camera that may be purchased. Using a box that is artificially lighted in a controlled setting, the photographs are shot to ensure uniformity in position, size, and lighting.

Dataset Collection

Dataset construction is also included in this study for training a multi-class insect infestation network. Mango trees across the Indonesian archipelago are sampled for data since the spread of a pest infestation is highly dependent on the particulars of the surrounding environment and the affected farm.

Identification of Insect Pests Dataset Ip102

In Wu *et al*. (2019), the IP102 insect pest identification dataset was used and the performance of the model was assessed. The 75,222 photos in this collection illustrate the 102 frequent bug issue categories. The crop types are divided into super-classes and Economic Crops (EC); further, they are divided based on plants affected by pest insects, which will make up the hierarchically organized IP102 dataset.

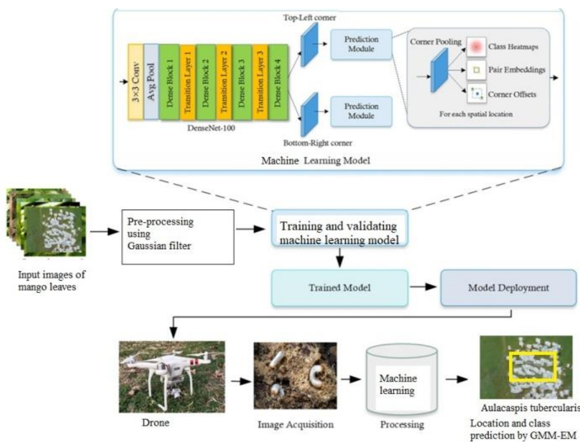


Fig. 1: Illustration of workflow for pest identification

Fig. 2: Samples of six different pest types in mango leaves

Figure (2) presents a variety of samples from the data collection that give a general overview of the various pest types and the quantity of associated image samples gathered from Indonesia.

Six distinct groups of pests that are known to impact mango farming the most are being examined and assessed in the study reported in this publication. The chosen six pest categories also cause structural deformity in mango leaves, which helps farmers quickly stop the pest's spread throughout the farm.

These six pests Apoderusjavanicus, Ceroplastesrubens, Mictislongicornis, Ischnaspi slongirostris, Aulacas pistubercularis, and Neomelichariasparsa have been recognized as a danger to the economic well-being of trade partners like Australia. They are often found in Indonesia.

Figure (2) images are collected from diseased leaves from mango farms, showing the fundamental information. The obtained pictures are cropped to only show a portion of the pest-specific property to emphasize the pests' visual traits. Real-time photos captured from sick leaves are employed in the research.

During the testing step, suspect samples are put into the trained framework to see how well the model is doing. The Corner Net model that is more closely based on the DenseNet-100 has been suggested. In order to choose the right category and find pests on plant leaves, Corner Net first computes the deep features from the input photos using the DesneNet-100 framework. The performance is assessed using a range of item detection criteria that are often used in the sector in the final stage. Figure (1) depicts the organizational layout of the recently created pest detection and classification technique.

For ML-based model training, the Region of Interest (RoI) must be precisely defined. To achieve this, the examples using the Labelimg tool are created (Lin, 2020). The samples contain information that is stored in an XML file and defines the location and class of each problem. The model is then trained using the final training files created from those XML files.

Preprocessing

Ideal, Gaussian, and mean are the Low pass filters used when preprocessing pictures in frequency, spectral, or spatial domains. Calculations are incompatible, and even though their application is fairly straightforward, it occasionally necessitates the conversion of images to grayscale or applying to each color channel separately (methods that are unable to be used in this research). As a result, it is decided to add a Gaussian filter to the original photographs of mango leaves using machine learning and the Fourier Transform.

Similar to monochrome images, color images utilizing hypercomplex numbers may be filtered in many different ways in the spectrum or frequency domain. The original approach really includes calculating the Fourier transforms of each image independently after dividing color images into 3 scalar pictures. Colored image Fourier transforms are uncommon.

Equation (1) illustrates the Quaternion Discrete Fourier Transform (QDFT):

$$F(u,v) = \frac{1}{\sqrt{MN}} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} exp(-j2\pi \frac{mu}{M}) f(m,n)\, exp(-k2\pi \frac{nv}{N}) \quad (1)$$

where, M represents rows, N represents columns, and MN is the dimension of a discrete array $f(m,n)$.

The inverse is defined as follows:

$$f(m,n) = \frac{1}{\sqrt{MN}} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} exp(j2\pi \frac{mu}{M}) F(u,v)\, exp(k2\pi \frac{nv}{N}) \quad (2)$$

By simply altering the complex exponential sign, it can be evaluated using the same code. A quick algorithm can evaluate the QDFT because it is separable.

In this study, multiplication in the spatial frequency domain is used to filter a color image of mango leaves. The inversed transformed picture will undergo the expected filtering when the QFFT transform image is multiplied by a filter's spatial frequency response.

In this example, a two-dimensional Gaussian low pass filter transfer function with a cut-off frequency at a distance δ serves as the filter's initial acquisition:

$$H_q(u,v) = \begin{cases} 1, & D(u,v) \le \delta \\ 0, & D(u,v) \ge \delta \end{cases} \quad (3)$$

where, δ is a gauge of the Gaussian spread, and $D(u, v)$ is the distance between the frequency rectangle ($M/2$, $N/2$) and the point (u, v):

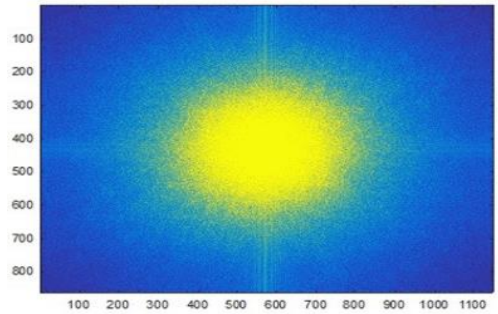
$$D(u,v) = \left[\left(u - \frac{M}{2} \right)^2 + \left(v - \frac{N}{2} \right)^2 \right]^{1/2} \quad (4)$$

The filtered image can then be produced using the filtered QDFT, which is produced by multiplying *2D*-QDFT of original images by QDFT and filter as shown in Fig. (3).

Feature Extraction

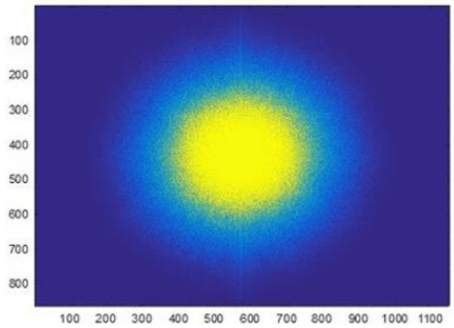
Corner Net Design

By using key point estimation, the Region of Interest can be detected using the Corner Net (Law and Deng 2020).



(a)

(b)



(c)

(d)

Fig. 3: (a) Original quaternion picture in the frequency domain; (b) Aulacaspis Tubercularis Original image; (c) QDFT applied image and; (d) Aulacaspis Tubercularis Resultant filtered image

In contrast to earlier anchor-based techniques, it predicts Bottom-Right (BR) and Top-Left (TL) corners in order to construct bounding boxes (b box), which are more accurate and effective. The prediction head and backbone network are two main parts of the Corner Net model.

The model first builds a set of interconnected key point maps using a backbone feature extractor network in order to class, offset, and embed forecast and Heat Maps (HMs). The HMs show how likely a specific location is to be a TL/BR corner for a specific class. Corner pairs and offsets are the main goals of the embeddings. The embedding distances on feature pairs are used for classification. The Corner Net model frequently performs better than the widely used methods for object identification.

In comparison to other things, insects provide a distinct classification and item identification problem due to their tiny size and resemblance to their surroundings in appearance. The Corner Net model is modified for this study to allow the identification and categorization of various pest species. The Corner Net model's principal feature extractor network is improved in order to enhance model performance and deliver more precise results for pest recognition.

Increased precision and efficiency in pest classification are the results of the improved backbone's computation of high-level discriminative data. The improved architecture is also more computationally effective and lighter than the old Corner Net model.

The Corner Net model's better reliability in detecting objects using key point estimates than earlier models is what drives its application to identify pests (Redmon and Farhadi, 2018). In contrast to earlier one-stage object recognition algorithms like YOLO (*v*2, *v*3) (Redmon and Farhadi, 2018) that require vast anchor boxes for a range of target dimensions, the model employs exact properties to detect the item. The suggested method is computationally effective since it divides the task of item identification and classification into two parts. The proposed methodology is well suited to address the problems since it provides a trustworthy framework that provides accurate picture features and also reduces the estimated cost.

Model for a Specific Corner Net Feature Extractor

A backbone network is used to extract the visual features that best represent an image. The flaw makes for a more manageable target. As a result, they necessitate more fine-grained and distinguishing features to set them apart from their convoluted environments, which include things like acquisition angles, brightness, and blurring. Rather than using the tried-and-true Corner Net model, this study opted for the more flexible Hourglass104 model (Law and Deng, 2020). However, the detection process is slower, and the model's overall efficiency is reduced due to the computational cost of the Hourglass network's need for a large amount of space and network parameters. The precision of the feature extractor also affects detection accuracy (Zhao *et al*., 2019).

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The Feature Extractor Densenet-100

Hourglass104 is deeper than Dense Net-100, which is made out of four densely linked blocks with 100 layers. The DenseNet-100's functionally basic architecture is shown in Fig. (3). With 7.08 M parameters compared to the Hourglass104 network's 187 M parameters, the Dense Net 100 architecture is more computationally efficient. Key point mappings from lower layers in Dense Nets are sent to higher levels through direct connections between all layers. The Dense Net architecture is well suited to handle complex modifications for pest localization because it encourages feature reuse and improves network information flow. Table (2) elaborates on the Dense Net-100's structural specifics.

The Dense Net structure consists of a Dense Block, a convolutional layer, and a Switching Layer. The Dense block structure, which is an important element of the Dense Net, is shown in Fig. (3). As shown in Fig. (4a), the 3×3 Convolution filter, batch normalization, and re LU are the three sequential operations that make up the compound method (H_n) (.). *F* key point maps are created by each H_n (.) process and then sent to *z n* further layers. Since the maps from all previous layers are fed into each layer of DnB, this results in the ingestion of $f(n1) + f_0$ feature maps at any layer of Dense block, which can increase the dimension of the map. Sandwiching *TnL* layers between DnB levels reduces the size of the map. According to Fig. (4b), the *TnL* is made up of an average pooling layer, a 1×1 Con *L*, and a *BtN*.

Table 2: Configuration of Dense Net-100

Name of the layer	Filter size	Stride
Convolution	3×3 Convolution	2
pooling	2×2 average pooling	2
Dense block(1)	$\begin{pmatrix} 1\times1\ con \\ 3\times3\ con \end{pmatrix}\times12$	1
Switching layer (1)		
convolution	3×3 convolution	1
pooling	2×2 average pooling	2
Dense block(2)	$\begin{pmatrix} 1\times1\ con \\ 3\times3\ con \end{pmatrix}\times12$	1
Switching layer (2)		
convolution	3×3 convolution	1
pooling	2×2 average pooling	2
Dense block(3)	$\begin{pmatrix} 1\times1\ con \\ 3\times3\ con \end{pmatrix}\times12$	1
Switching layer (4)		
convolution	3×3 convolution	1
pooling	2×2 average pooling	2
Dense block(4)	$\begin{pmatrix} 1\times1\ con \\ 3\times3\ con \end{pmatrix}\times12$	1
Prediction layer	7×7 average pool fully connected layer	

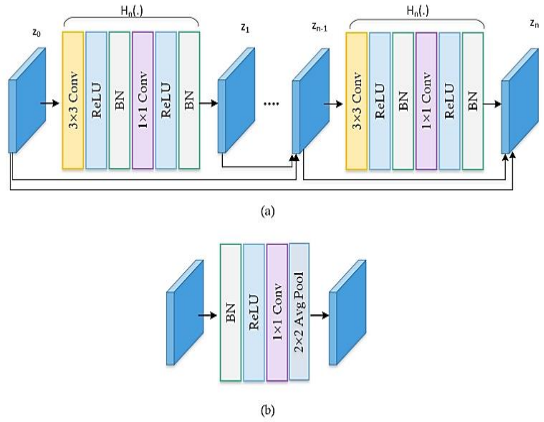


Fig. 4: Structure of DenseNet-100; (a) Transition block and; (b) Dense block

Two unique output branches represent the corners (TL and BR) of the prediction branch after the feature extractor network. Each module has a pooling layer that collects features and produces HMs, embeddings, and offsets on top of the backbone. Following the prediction module, the corner pooling layer is introduced. It is made up of a residual block with two 3×3 Convolution and one 1×1 residual network. The corner pooling layer aids in more accurate corner localization for the network. Following the transmission of the features, a 3×3 Convolution-BN layer is reverse projected. Following this residual block, a 3×3 Convolution that outputs HMs, embeddings, and offsets is applied.

Prediction Module

The corner points are approximately found using the HMs. Since there is a quantization problem when key points from the input picture are transferred to the feature map, offsets are used for corner placement. There may be several defects in a single photograph. If a point belongs to a group, then the embeddings can be used to determine whether the corners are connected with pests.

Corner Recognition

By utilizing a 3×3 max-pooling layer and Non-Maximal Suppression (NMS) on the corner HM, the box is generated from the corner predictions. The HMs are used to choose the top 100 corners across all classes. The corner placements are modified using the anticipated offsets couples. Then, the offset couples with an L1 distance higher than 0.5 are disregarded when matching the TL corner and BR corner with the most similar embedding for each class. By using soft-NMS, overlapped boxes from the generated candidate box are eliminated significantly. The detection scores are calculated using the average of corner values.

Loss Function

The multi-task loss approach employs an end-to-end learning system and corner Net to improve performance. The following four separate losses are added together to form the training loss function L.:

$$L = L_{\det} + \alpha L_{pull} + \beta L_{push} + \gamma L_{off} \tag{5}$$

where, L_{det}, a type of focal loss, is responsible for corner detection; L_{pull}, a type of grouping loss, is in charge of grouping corners of the same bbox; L_{push}, a type of corner separation loss, is in charge of separating corners of different bboxes; L_{off}, a type of smooth; and $L1$, a type of loss, is in charge of offset correction. The pull, push, and offset loss weight parameters, denoted by the letters of the variables α, β, and γ are set to $\alpha = \beta = 0.1$ and $\gamma = 1$, respectively. The L_{det} is illustrated as:

$$L_{\det} = \frac{-1}{M} \sum_{i=1}^{C} \sum_{x=1}^{H} \sum_{y=1}^{W} \begin{cases} (1-T)^{\varphi} \log(T) & if\,(G)=1 \\ (1-G)^{\omega}(T)^{\varphi} \log(1-T) & otherwise \end{cases} \tag{6}$$

The letter M indicates how many bugs are visible in the photograph. The letters C, H, and W stand for the input's channels, width, and height, respectively. G_{ixy} is the equivalent ground-truth value, and T_{ixy} is the predicted score for a pest of class I in the input picture at the position. T and G stand for T_{ixy} and G_{ixy}, respectively. The hyperparameters ϕ and ω, which are set to 2 and 4, respectively, define the contribution of each point.

Downsampling reduces the image's size such that it is smaller than the original input image. Given that downsampling factors n, a pest's position in the input image (a, b) is translated to a pest's position in the HMs (a/n, b/n). Locations are inaccurately remapped from HM to the original input size picture, thus lowering the IoU quality for smaller boxes. After that, the corner locations are modified using the calculated position offsets, which are supplied as:

$$O_k = \left(\frac{a^k}{n} - \left\lfloor \frac{a^k}{n} \right\rfloor, \frac{b^k}{n} - \left\lfloor \frac{b^k}{n} \right\rfloor \right) \tag{7}$$

where, the estimated offset and coordinates of corner k's a and b are denoted as a^k and b^k, respectively. The $L1$ function, which is used to subtly alter the corner placements for training purposes, is described as follows:

$$L_{off} = \frac{1}{M} \sum_{k=1}^{M} Smooth\,L1\ Loss(O_k, O_k') \tag{8}$$

In a single image, multicorners are calculated due to the possibility of various faults in an input image. For each corner, the network can predict an embedding vector that is recognized in order to ensure that a pair of corners is used to identify pests. To train the network, the "pull" and "push" losses are reused, which are shown as follows:

$$L_{pull} = \frac{1}{M} \sum_{i=1}^{M} [(e_{li} - e_i)^2 + (e_{ri} - e_i)^2] \tag{9}$$

$$L_{push} = \frac{1}{M(M-1) \sum_{i=1}^{M} \sum_{j=1}^{M} \max[0, \Delta - |e_i - e_j|]} \tag{10}$$

If e_i is the average of E_{li} and e_{ri}, then E_{li} stands for the TL corner and e_{ri} represents the corner for Pest i. For the purposes of the study, $\Delta = 1$ is selected as the maximum distance between any two corners that have different kinds of bugs.

To accomplish the mango plant leaf disease classification, this study consists of two primary processes. First, the annotations are created using the photos from the IP102 dataset in order to appropriately identify the impacted areas and the classes that go with them. By creating a bounding box (box) around the unhealthy sections of the leaves, these annotations help to precisely outline those locations. The DenseNet-100-based Corner Net method is then trained using these annotations. The test phase uses the test set's photos to verify the model's effectiveness. By incorporating the DenseNet-100 network in the Corner Net model's feature extraction unit, this study has more specifically modified the Corner Net model. The Corner Net model receives the computed feature vector from the DenseNet-100 approach's base network, which then uses it to locate and divide the impacted areas into six groups. The effectiveness of the newly introduced framework is then statistically evaluated using a number of accepted assessment metrics. Algorithm 1 provides a full model formulation of the framework, and Fig. (1) provides a visual demonstration of the approach's specific phases.

Classification

Gaussian Mixture Model and Expectation-Maximization (EM) Algorithm

GMM is used while doing a cluster analysis. A form of unsupervised learning called clustering assigns a single class and corresponding feature vector x_n to each pixel based on where it is located in the feature space. The data is divided into K groups of pixels to do this. In order to create sets of clusters, the estimated distances between pixels are utilized as a benchmark. The K-means approach is used to initialize the GMM.

Algorithm 1: Custom Co Net with Dense Net 100 algorithm for mango leaf pest feature extraction

Input: TS, I
Output: *Bbox*, Custom Co Net, C-score
TS-Number of training samples
I–Pest area in mango leaves
Bbox-rectangular box showing the affected region
Custom Co Net Corner Net model and Dense Net-100
C-score confidence and predicted class
Sample size ← [*x y*]
Bbox calculation
β ← Anchor box Calculation (*TS*, *I*)
Custom Custom Co Net-Model
Custom Co Net ← CornerNetWithDenseNet-100(*Sample Size*, β)
[d_r d_t] ← Dataset is partitioned into training and test data
Training module-disease detection and classification
For each image m in → d_r
CalculateDenseNet-100-Based-Features ← *df*
End For
Training and measuring network training time
β _ *dense* ← Estimate Pest Diseased Pos(*df*)
V _ dense ← Model _ Validation (*DenseNet*-100, β_*dense*)
For each image *M* in → d_t
i. Measure features with the model €→*V_dense*
ii. [*Bbox, C-score, class*] ← Predict (€)Present output pest diseased labeled image with B*box, class*
iii. (iv) η ← [η *Bbox*]
End For
Ap_€ ← Test framework € using η
Output _ class ← CustomCoNet (*Ap_€*)

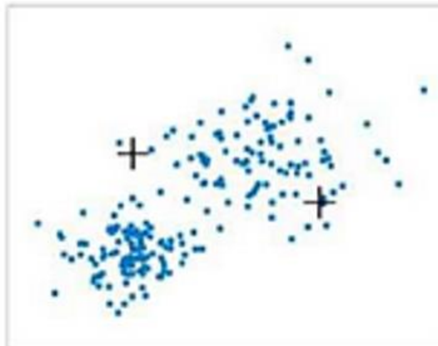
K-Means

In this study, the K-Means algorithms are used as a simple cluster technique to correctly pre-process images of mango leaf pests. A set of K cluster centers. *M* is the average value of each point in the k^{th} cluster that is stored in memory for the purpose of performing its operation.

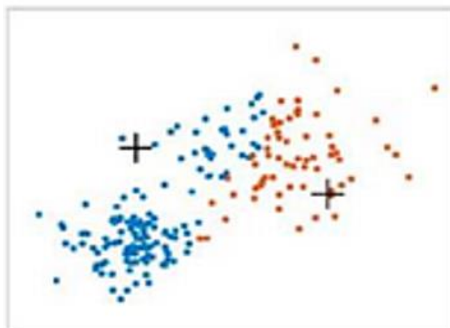
EM Algorithm

The Expectation-Maximization (EM) technique is utilized in Fig. (5) (a) to learn the cluster centers of images of the mango leaf pest. Each pixel is assigned to a cluster close to the center (E-step) after initializing the cluster centers at random (+), and the centers are recalculated (M-Step). An objective function's improvement is gradually decreased until it is below a certain level. K-means is a type of hard clustering, each pixel in an image of a mango leaf pest is allocated to precisely one non-overlapping cluster, and pixels that share attributes, more than two groups are disregarded:

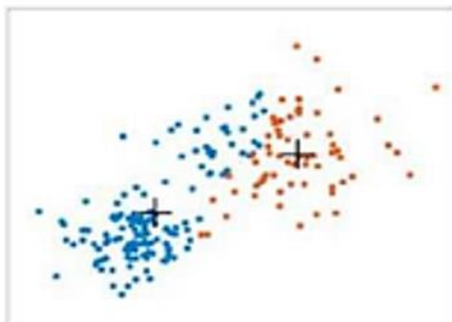
a) Initialization (k-means)
b) E-step (k-means)
c) M-step (k-means)
d) Initialization (GMM)
e) E-step (GMM)
f) M-step (GMM)



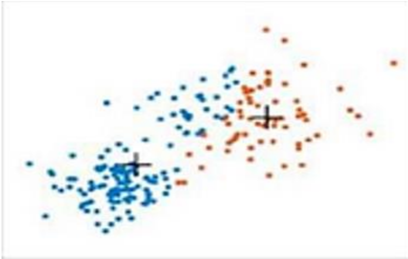
(a) Initialization (k-means)



(b) E-step (k-means)

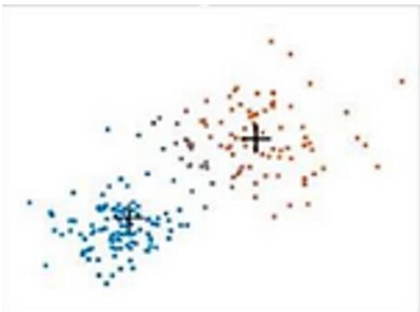


(c) M-step (k-means)



(d) Initialization (GMM)

(e) E-step (GMM)



(f) M-step (GMM)

Fig. 5: Clustering of mango leaf pest using GMM-EM algorithm

The Expectation Step (E) and the Maximization Step (M) are the two key phases of the EM algorithm.

Step of estimation: Create μ_k, Σ_k, π_k 's initial values using random numbers, K-means clustering, or hierarchical clustering results. Then, the value of the latent variables is calculated using the given parameter values (γ_k).

Step of maximization: Update the parameter (μ_k, Σ_k, π_k) value determined using the ML technique.

GMM, is a type of soft clustering, partitioning the datasets into K different multivariate Gaussian distributions.

In hard clustering, a pixel is assigned to one cluster, whereas in GMM the posterior probability that a pixel belongs to each cluster $p(z_k = 1 | x_n)$ is calculated and the pixel is assigned to the cluster that has the highest probability. A GMM uses the EM algorithm, as seen in Fig. (4d-e). The K distributions are initialized with the means like in the K-means algorithm; then, the posterior probabilities are calculated for each pixel (E-step), and, further, the Gaussian distribution parameters (μ_k, Σ_k,) are updated (M-step).

Figure (4d-e) shows the posterior probability in color, and the proportion of red and blue for each point is shown as posterior probabilities.

Algorithm 2: GMM-EM algorithm for mango leaf pest identification	
Input	Mango leaf images $XX=[x_1,x_2, \; x_n] \in R^{N\times D}$, where $x_N \in R^D$
Initialize	$\{\mu_k\}$ via K-means algorithm, $\{\Sigma_k\}$ and $\{\pi_k\}$ uniformly at random and evaluate log-likelihood $\ln p(X\|\mu,\Sigma,\pi)$ new $= \sum_{n=1}^{N} \ln\{\sum_{k=1}^{K} \pi_k N(x_n \| m_k, \sum_k)\}$
	Repeat:
1	$\ln p(X\| \mu,\Sigma,\pi)_{\text{old}}$ $\ln p(X\| \mu,\Sigma,\pi)$ new
	$P(z_k = 1\|x_n) := \ln p(X\|\mu,\Sigma,\pi)_{new}$ (E-step)
2	$p(z_k = 1 \| x_n) := \frac{\pi_k N(x_n \| m_k, \sum_k)}{\sum_{j=1}^{K} \pi_j N(x_n \| m_j, \sum_j)}$
3	$\Sigma_k := \frac{1}{N_k} \sum_{n=1}^{N} p(z_k = 1 \| x_n)(x_n - \mu_k)(x_n - \mu_k)^T$ (M-step) $\pi_k := \frac{N_k}{N}, \text{where } N_k = \sum_{n=1}^{N} p(z_k = 1 \| x_n)$
4	$\ln p(X \| \mu,\Sigma,\pi$ new: $= = \sum_{n=1}^{N} \ln\{\sum_{k=1}^{K} \pi_k N(x_n \| m_k, \sum_k)\}$
	Until converged;
Output	Classified Pests in mango leaves $p(z_{k=1} \| x_n)$ and $\mu_k \in R^D$, $\Sigma_k \in R^{k\times k}$, $\pi_k \in R$ which minimize the objective log-likelihood

Results and Discussion

Implementation Details

The proposed framework is implemented in Python and tensor flow. Table (3) shows a summary of parameters for the Custom Corner Net-based GMM-EM model.

To construct the model, hyperparameters are modified. Three learning rates (0.01, 0.001, and 0.0001) are used in the experiment. The chosen period and mini-batch size are 15, 25, 35, 45, and 16, 32, 64, respectively. The dropout value is adjusted at 0.3 to prevent overfitting. The input picture dimension is resized to 224×224, and the data are then randomly split into training, validation, and test data. The three categories produced from the remaining data are Testing (30%), Validation (10%), and Training (60%).

Dataset Description

The (IP02 Dataset (n.d.)) is used to evaluate the model performance. It is a benchmark dataset for identifying the pests in plant leaves. This dataset comprises a record of 75,222 leaf images with 102 pest classes. Each class includes about 737 image samples of leaves. Further, this dataset has eight superclasses in which the leaves of corn, wheat, rice, Alfalfa, and Beet belong to the field crop. Then, the plant leaves of Citrus, Vitis, and Mango are grouped under the Economic crop. The dataset is divided into training (45133 images 60%) and training (22566 images 30%), and 7522 images are adopted for the validation purpose. The link for the dataset is also cited below in the reference list.

Evaluation Parameters

A variety of metrics like mean average precision, Intersection over Union (IoU), Accuracy (Acc), Recall (R), and Precision (P) have been used for assessing the suggested technology's performance. The following is the formula for these metrics:

$$P = \frac{TP}{(TP + FP)'} \tag{11}$$

$$R = \frac{TP}{(TP + FN)'} \tag{12}$$

$$ACC = \frac{(TP + TN)}{(TP + TN + FP + FN)'} \tag{13}$$

$$IoU = \frac{TP}{(FN + FP + TP)} \times 2 \tag{14}$$

$$mAP = \sum_{i=1}^{T} \frac{AP(t_i)}{T} \tag{15}$$

$$F1\_score = \frac{2PR}{P + R} \tag{16}$$

In the above Eqs. (11-16), True positive, True Negative, False Positive, and False Negative instances are denoted as *TP*, *TN*, *FP*, and *FN*, respectively. The formula to calculate *mAP* is given in Eq. (12), where t stands for the test picture, *T* for all the test images, and *AP* for the average precision of each class.

Cross-Validation

The *K* clusters and *Npc* number of principal components used during training may have an impact on the accuracy. Thus, the parameters are modified using a cross-validation set. F1-score was used from the cross-validation set, and the accuracy was calculated after training on all *K* = 1, 2,...10 and *Nc* = 1,2,.....10 pairings.

Tp represents the % of pixels that are correctly assigned to the mango leaf cluster, *fp* represents the percentage of incorrectly assigned pixels to the mango leaf cluster, FN represents the % of incorrectly assigned pixels to a portion of the infected mango leaf cluster, and c represents the cluster with the highest percentage of manually labeled pixels that correspond to the infected mango leaf cluster.

Results of Localizing Insect Pests

While developing an automated pest identification approach, the localization of pests is crucial. As a result, the proposed framework that can be localized is created. The analysis of the test pictures using the test images in the IP102 dataset produces the GMM findings, which are depicted visually in Table (4).

It is inferred from the published findings that the suggested technique is effective at finding pests of different sizes and shapes. The proposed framework can localize by using a key point estimate, which enables distinguishing the pests of different types accurately. To evaluate the effectiveness of localization, *mAP* and *IOU* are calculated. These tests show how precisely the suggested approach classifies and detects different pest species. If the overlap score between the projected area and the actual location is less than this amount, it is considered background; if not, it is considered a pest. The Intersection Over Union threshold is set at 0.5 for localization. Mean *IOU* and *mAP* values of 0.578 and 0.621, respectively, were produced using the recommended framework. These findings suggest that the suggested method may be able to locate pests accurately and successfully even in environments with diverse backgrounds.

Table 3: Training parameters for the proposed model

Framework parameters	Value
Epochs	35
Unmatched threshold	0.5
Confidence score threshold	0.5
Batch size	64
Learning rate	0.0

Table 4: Performance analysis of the proposed method for identifying different pest classes

Mango leaves pests	Classified Images	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Apoderus javanicus		59.3	54.87	42.23	47.7
Ischnaspis longirostris		69.5	57.86	51.55	54.5

Table 4: Cont.

Aulacaspis tubercularis		49.7	59.37	53.61	56.3
Mictis longicornis		89.9	79.94	75.82	77.8
Ceroplastes rubens		77.3	74.87	70.28	72.5
Neomelicharia sparse		85.1	80.25	77.31	78.7

Accurately classifying various pests is essential to demonstrating a model's dependability. Pests may come in a variety of forms depending on the type of mango leaves grown in the area. All test images from the IP102 dataset are applied to the trained CornerNet model and GMM-EM to complete this assignment. The classification of pests based on crops used in the recommended strategy is shown in Table (4).

The results show that the presented framework GMM with $K = 2$ and $Nc = 6$ outperformed all other hyperparameter combinations, achieving the best *F1*-score of 77.8% for Mictis longicornis pest identification with 89.9% accuracy, 75.82% recall, and 79.94% precision.

The effectiveness of the employed key points computation technique, which accurately and reliably represents each pest class, is the cause of the robust pest classification performance. The effectiveness of the suggested method is demonstrated by the performance of the distinctive Corner Net model and GMM-EM in mango leaf-wise pest identification. A chart in Fig. (6) shows the metrics of six mango leaf-wise pest classes.

Figure (5) shows the distribution of categorization metrics across several classes. This method obtained an average accuracy of identifying the six mango leaf pests as 0.593, 0.695, 0.497, 0.899, 0.773, and 0.851. By achieving a low mistake rate and an average classification accuracy of 0.7166 across all classes, this study was able to illustrate the advantages of the suggested strategy more clearly. The recommended framework can only achieve mediocre classification accuracy on the mango leaf pest Aulacaspis tubercular because of visual resemblances to the background and significant intra-class variability.

DenseNet-100 Model Analysis

When utilized for photo identification, deep qualities are effective. The research was done to compare the DenseNet-100 model to other models for identifying pests. As a result, a number of base models, including Inception V4 (Alom *et al*., 2020) and Efficient Net (Atila *et al*., 2021), are used to assess how well the proposed Custom Corner Net performs in terms of detection. The generalizability of this model is increased to novel data using transfer learning. On the IP102 database, all of these important networks have already been pre-trained and perfected. The networks were trained in this experiment across 30 epochs with mini-batch sizes of 16 and 64. It has been investigated how well the models perform in categorizing data from the IP102 database as well as how difficult their calculations are done using network parameters. Table (5) compares the strategy with a number of feature extraction models.

This demonstrates that the classification is precise. The results demonstrate that the custom Corner Net, which uses the DenseNet-100 as its backbone network, outperforms earlier models. This is due to the Dense Net model's rapid computation of deep features and capacity to provide a more precise and diversified feature. The accuracy of the Efficient Net model is a second representation of a wide range of insect problem species. From Table (5), two important frameworks for pest identification that perform badly are Efficient Net and Inception v4. This might be a result of a high rate of misclassification brought on by their inability to distinguish between several bug species in a complex environment. Inception V4 has the lowest accuracy rate

(47.2%) when predicting pests across 6 categories. The primary reason the model performs poorly is that the network is too simplistic to pick up on subtleties like the texture of the input data. However, they continue to do poorly when it comes to categorizing various pests. Due to different network properties, these models are likely to overfit in the IP102 dataset. The proposed model proves that it is superior to other models based on an accuracy of 89.9% for classifying the pest species (Mictis longicornis). It does, however, provide more computational challenges. In contrast, the Dense Net-100 contains fewer parameters than any other DL model that has been used, with a total of 7.08 million. Due to the enhanced network architecture of the technique, which allows for the highest possible reuse of model parameters, pest classification performance is increased. This study chose them over the original basis model implementations due to their simpler structures and ability to extract trustworthy features. By reusing characteristics from earlier layers in each subsequent layer and utilizing a robust framework for creating discriminative key points, this method gets around the drawbacks of comparison models. As it appropriately manages complicated modifications, it performs better. According to this research, the recommended custom Corner Net performs more accurately and effectively than prior feature extraction models. It uses the DenseNet-100 framework.

Performance Evaluation of ML-Based Classifiers

The experiment was conducted to show performance with other classifiers to ensure the efficacy of the proposed technique and contrast its performance with ML-based classifiers employing deep features. The IP102 dataset was split into training, validation, and testing sets, which collectively made up 60, 10, and 30% of the overall dataset, respectively.

The three most effective feature extraction models from Table (5) were used to extract the machine learning features. The correct classification results from training KNN using the ML features from ResNet-50 (He *et al*., 2016) and Efficient Net (Atila *et al*., 2021) are given in Table (6).

Table (6) shows that using the Custom Corner Net-based machine learning features with the KNN classifier produced better results compared to other combinations. The best outcomes were still attained by the Custom Corner Net model. To be more precise, the accuracy of the suggested Custom Corner Net model was 89.9% compared to 60.2% for Efficient Net with KNN as back-end classifiers. This suggested that the proposed model performed better than an ML-based classifier at handling over-fitted training data and provided a more accurate feature representation of the pests.

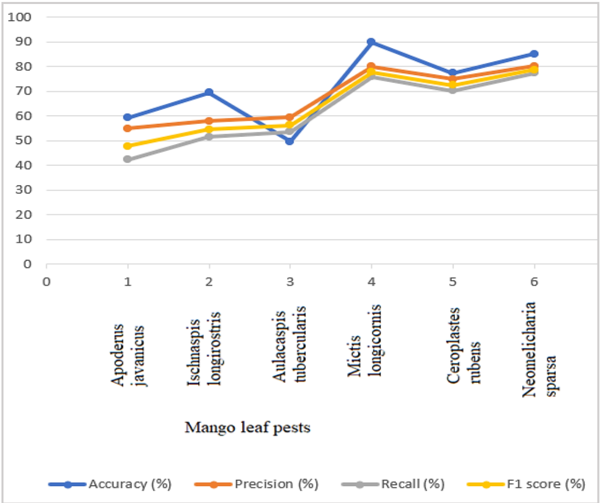


Fig. 6: Analysis of the proposed method for pest identification

Table 5: Performance evaluation of the proposed feature extraction over the baseline methods

Mango leaves pests	Parameters (million)	Accuracy (%)
Inception V4	41.2	47.8
EfficientNet	19.4	60.2
DenseNet-100 (Proposed)	7.08	89.9

Table 6: Performance comparison of proposed and existing ML classifiers in pest detection

Methods	Accuracy (%)
	KNN classifier
ResNet-50	49.4
Efficient Net	60.2
Custom Corner Net (Proposed)	89.9

Table 7: Performance assessments of suggested strategy and previous methods

Reference	Method	Accuracy (%)
Reza *et al.* (2019)	InceptionNetV3	57.08
Ayan *et al.* (2020)	GAEnsemble	67.13
Zhou *et al.* (2020)	EquisiteNet	52.32
Ren *et al.* (2019)	FR-ResNet-50	55.24
Liu *et al.* (2020)	DFF-ResNet-82	55.43
Proposed	CornerNet-DenseNet-100	89.90

Performance Evaluation in Relation to Current Methods

This section compares the performance of the proposed method with other baseline models (Reza *et al*., 2019; Ayan *et al*., 2020; Zhou and Su, 2020; Ren *et al*., 2019; Nanni *et al*., 2020) using the same dataset, IP102 (Wu *et al*., 2019). The results of pest classification are shown in Table (7) based on accuracy.

The Corner Net architecture uses computed features to categorize the pests. As a consequence, the recommended model performs much better when the pest is classified and recognized in the difficult dataset IP102. In addition to being computationally effective and reliable, the proposed technique allows for a more accurate identification of insects than existing approaches. Therefore, it is revealed that the proposed strategy has a lot of potential for the drone-based field categorization of target pests.

Conclusion

The automated field identification and classification of mango leaf pests with drone aid is presented in this study as a low-cost Machine Learning (ML) based approach. The suggested technique used a backbone network of Dense Net for feature extraction based on a unique Corner Net model. More precisely, a set of key points was developed that could be utilized with the DenseNet-100 network to discriminate between the input samples. By using GMM-EM, the Corner Net model was customized and trained to recognize different pest species. This approach was tested using the IP102 dataset, which was a huge and difficult benchmark database for pest identification consisting of in-field collected photographs. Through careful testing, it was proven that this method was applicable to real-world pest monitoring applications. The results showed that the presented framework GMM with $K = 2$ and $Nc = 6$ outperformed all other hyperparameter combinations, achieving the best F1-score of 77.8% for Mictis longicorn pest identification with 89.9% accuracy, 75.82% recall, and 79.94% precision. The published findings demonstrated that, even in the presence of complicated backgrounds and changes in insect form, color, size, orientation, and brightness, this system could reliably locate and categorize pests of different kinds. As every method had its own drawbacks, the proposed work also had some limitations, which were further mentioned. Even though the enhanced model was established for the effective pest identification of mango crops, only a limited number of pests were detected. Also, focusing on a single crop could not assist the vegetation growth of the agricultural domain. Moreover, the optimal features were not selected for the model training, which slightly increased the computation time. These were some of the notable downsides of the proposed methodology.

Future Work

In order to further improve the performance of the proposed research, the study will be intended to establish deep learning-based fine-grain pest categorizations in the future by developing a more effective feature fusion strategy. Moreover, multiple diseases in different plants will be focused on in the future using the advanced Deep learning technique. Apart from mango plant leaf, other significant crops like potato, soya, corn, tomato, and so on will be considered and various types of diseases or pests will be classified to effectively detect the plant leaf diseases in the future. Furthermore, feature analysis will be concentrated in depth to learn the feature relationship among different leaves, resulting in more accurate pest identification of plant leaves. Thus, crop diseases will be effectively managed in the agriculture sector by detecting the pests in advance by extending the proposed work in the future.

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Author’s Contributions

D. Lita Pansy: The first draft of the manuscript, Contributed to the study conception and design. Material preparation, data collection, and analysis were performed.

M. Murali: Contributed to the study conception and design. Material preparation, data collection, and analysis were performed.

Ethics

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of Data and Materials

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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