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Review Article

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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR THE PEST DETECTION IN BANANA FIELD: A SYSTEMATIC REVIEW

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ABSTRACT

Purpose: This systematic review details the diseases that influence banana production and their detection. A common method for identifying plant diseases in plants is image processing. Segmentation is one method for using image processing to establish medical diagnosis. The main objective of this study is to identify, categorize, and evaluate several image processing techniques used to control pests in a banana crop.

Methodology: An electronic search was conducted using relevant keywords on openly available databases including IEEE Xplore, PubMed, Science Direct, and Google Scholar. 104 items were discovered by the search engine. After removing the duplicates, there were 56 research papers remained, but 22 of them were discarded after title and abstract checks since they did not address insect detection in banana fields.

Results: 22 papers that come under the headings of image classification, AI/ML, deep learning, and mobile applications provide usable and reliable detection techniques in this systematic review.

Keywords: pest, banana, detection, plant, disease

INTRODUCTION

Global hunger and food insecurity are mostly caused by crop diseases. Up to 16 percent of agricultural output losses worldwide each year are really caused by plant diseases. Several diseases, such as banana sigatoka and banana speckle, are endangering the yield of bananas. A method to automatically categorize and diagnose banana maladies is urgently needed due to the global shortage of resources and knowledge on banana pathology (Oerke, 2006)

Figure 1: Banana pests

In terms of both production volume and commerce, bananas are among the most significant fruit crops in the world. Only 13% of all bananas produced are exported, despite being a crucial staple crop throughout Africa, Asia, and Latin America. This clearly illustrates how crucial fruit is for local markets and food security. Artificial intelligence (AI) that use deep learning techniques to diagnose plant illnesses based on the look of the vegetation and vision problems that match people's behavior should be considered seriously. Smartphone AI applications might warn farmers and speed up disease detection, perhaps slowing the spread of diseases and pests. Despite the fact that many farmers in less developed nations lack access to this cutting-edge equipment, the growth of the internet and the popularity of smartphones have given rise to new methods for diagnosing agricultural diseases in the field (Camargo & Smith, 2009).

An important challenge is the automated categorization of photos of sick banana leaf plants. Deep learning algorithms may be used by farmers to recognize and diagnose the disease. When compared to image processing and machine learning methods, deep learning's categorization of images of damaged banana leaves yields reliable findings. There are now just handwritten features available, which often need significant human input and cannot be utilized for all types of data (Saleem, Potgieter, & Arif, 2019).

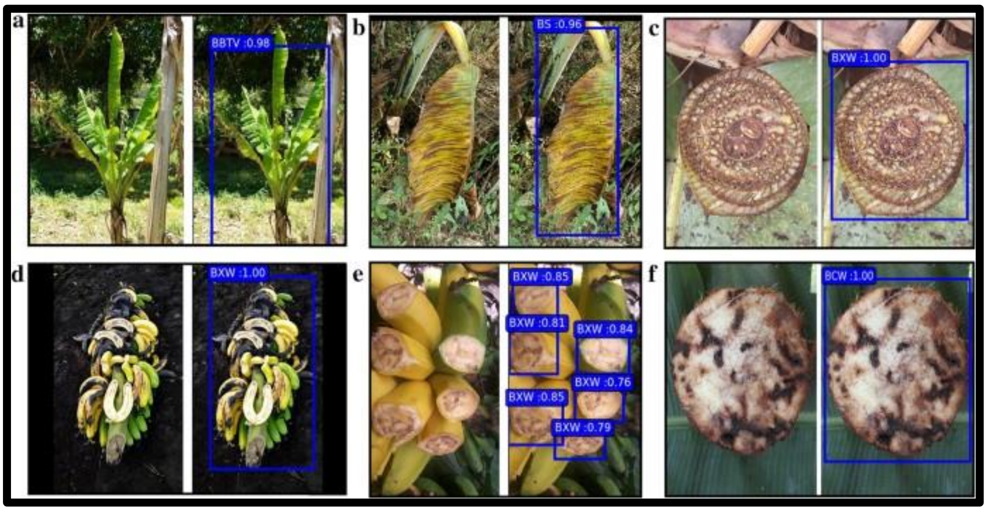

Figure 2: AI powered pest detection

Food is essential to human life, and agriculture is one of the major economic drivers in any given nation. Most developing nations' primary source of revenue is generally acknowledged to be agriculture. Because bananas are an excellent source of minerals including calcium, manganese, potassium, magnesium, and iron, banana cultivation and the banana industry are significant components of the worldwide agro-business. Because bananas are regarded to be an immediate energy booster, people eat this specific crop because it includes so many vitamins. According to Wikipedia, around 15% of the world's banana output is exported for consumption in western nations. According to data on banana export and production, India accounts for around 25.7% of global banana output. Other prominent banana-producing countries are the Philippines, Ecuador, Indonesia, and Brazil; together, they account for around 20% of global banana output. With 18% of all international imports, the United States is the primary market for bananas. Banana output and export may even completely decline as a consequence of disease and other weather factors affecting banana plants. The four main illnesses that often afflict bananas are Black Sigatoka, Xanthomonas wilt, bunchy top virus, and fusarium wilt, sometimes known as Panama wilt (Uwamahoro, Berlin, Bylund, Bucagu, & Yuen, 2019).

Most farmers don't have a formal education, thus they often don't have a clear grasp of plant diseases and require professional help. The manual prediction approach is not very accurate since plant pathologists cannot visit every farm and must depend on human eye evaluation. Therefore, it is crucial to develop an autonomous leaf disease detection system that aids farmers in more accurate and early disease identification (Karmokar, Ullah, Siddiquee, & Alam, 2015).

Crop diseases do a lot of harm and have a negative impact on crop productivity and quality. They are often brought on by nematodes, bacteria, fungus, viruses, and nutritional deficiencies. Water, wind, and air may all transmit plant diseases. Banana plants may have a variety of illnesses, which manifest as symptoms on the leaves and fruits. Black Sigatoka, Freckle, and Banana Bunchy Top Virus are the three leaf diseases. Anthracnose, freckles, and crown rot are the three fruit diseases. The most advanced tools for evaluating the yield, health, and economic value of the crop are now available thanks to UAVs and satellites that can take a huge number of exceptional spectral-temporal aerial photographs. Successful classification techniques for many types of crops include support vector machines (SVM), K-nearest neighbors (KNN), and maximum likelihood classification (MLC). These processes take more time and need supervised labelling in order to provide accurate data, however. Therefore, it is crucial to provide viable crop categorization systems with a range of applications in difficult operating conditions. It may be challenging to identify crops using remote sensing, particularly when they exhibit identical spectral responses and growth patterns. Advanced machine learning methods and object-based image analysis may be used in these situations to improve categorization jobs (Peña *et al.*, 2014).

In order to optimize output, industrial crops need specialist management that provides the proper water and fertilizer inputs, analyzes crop condition, and finds pests or disease. Crop managers need to consider the cost-return in relation to the scheduling and strength of treatments based on plant biology, structure, morphology, and biotic and abiotic factors since banana plants are regarded to be heavy feeders. The requirement to lessen the possibility of dangerous excess fertilizer runoff must also be taken into account in this delicate balancing act. For crop management assessments, visual assessment and simple scheduling are often employed in the field, and manually put markings on plants are utilized to direct subsequent actions. Since these activities primarily depend on a person's experience, they may be time-consuming, subjective, and unreliable (Swarupa, Ravishankar, & Rekha, 2014).

Plant health, vigor, illness, disease susceptibility, and yield have all been connected to morphological features including plant height, leaf area, leaf number, and crown size as well as physiological factors like leaf biochemical composition and internal structure. However, it takes a high degree of technical expertise to grow these crops with the best yield and productivity. In an attempt to naturally manage pests and illnesses rather of requiring pesticides, several research on greenhouse agro-systems and more broadly on protected crops have been carried out. The goal of agricultural research, which has recently gained popularity, is to boost output and food quality while spending less and making more money. In many nations today, there is a significant demand for non-chemical approaches to disease or pest management. However, there are currently no automated techniques that can accurately identify plant pests. In reality, workers in greenhouses keep a close eye out for pests in circumstances related to production. Manual labor is very time-consuming. It is now feasible to create an autonomous system for diagnosing crop illnesses thanks to recent developments in image processing and pattern recognition methods (Kobayashi, Kanda, Kitada, Ishiguro, & Torigoe, 2001).

A method that is often used to detect plant diseases in plants is image processing. Segmentation is one method for using image processing to diagnose illnesses. This segmentation method, which makes use of soft computing, offers rose, banana, bean, and lemon plants with an average accuracy of more than 80%. The average accuracy rate for a range of different image processing methods used to identify plant diseases is more than 65%. Additionally, there has already been investigation into specific image processing methods for spotting diseases in banana plants. By identifying and collecting the various intensities of infrared light produced by objects, thermal cameras measure temperature. If the intensity of this light—which is undetectable to the human eye—is great enough, it may be experienced as heat. The amount of infrared radiation that an item emits depends on its temperature. This radiation may be detectable by thermal cameras, which may then turn it into pictures. Infrared light, which the human eye cannot perceive, may be turned into a visible picture by a night vision camera, for example (Triwidodo, Tondok, & Shiami, 2020).

Only virus-carrying banana aphids and contaminated plant debris may infect banana plants. The BBTV may spread when individuals give away suckers or young banana plants to others. The aphid, a tiny black beetle, takes up residence on the BBTV after ingesting food from an infected banana plant. The BBTV may spread farther since aphids may travel great distances on the wind. After aphid inoculation, the time it took for BBTV symptoms to appear on banana plants varied from 25 to 85 days. Temperature and relative humidity are often useful in predicting some diseases and pests. Farmers schedule their activities, such as snowing, protecting, and harvesting, according to weather monitoring in order to minimize the effects of the weather and crop loss. Temperature, relative humidity, soil moisture, rainfall, and wind speed/direction are a few of the measurement choices available in weather monitoring that provide information on the soil, crops, and other objects. These characteristics may be used in agricultural tasks including timely irrigation, insect control, and fertilization. Reliance on meteorological data is essential for effective farm management in today's agricultural operations.

The scaling problem has also risen to the top of the list of remote sensing research problems as a result of scale effects. It is useless and unfeasible to seek out very high-resolution data for the agricultural application owing to exorbitant price and processing challenges, even if greater spatial resolution photos display more landscape aspects and more accurate predictions. It is preferable to choose an image with a suitable spatial resolution for agricultural monitoring after taking into account a number of parameters. Additionally, selecting the right data analysis technique is crucial since it has a direct impact on the precision and dependability of the outcomes. Bands and characteristics that are sensitive to crop disease detection and discrimination have been identified using a variety of methodologies or models.

Binary logistic regression (BLR), where the response variable is a binary variable that denotes whether an incident happened, is one of the most often used multidimensional analytic techniques. BLR is used to describe the relationship between dependent variables and a set of independent variables. Compared to linear analysis and log-linear regression, logistic regression offers advantages since it does not need the assumption of normality. The easiest method to recognize crop diseases is to heed the advice of an agricultural professional who has information that is supported by real world experience with the signs and causes of infections. Manually identifying agricultural diseases requires a deal of time and resources.

It is crucial to automation the diagnostic accuracy of plant diseases in order to maintain plants since the use of agricultural chemicals, which are environmentally harmful, is required to cure a variety of illnesses. An efficient protection strategy should start with an early diagnosing in order to choose the best treatment at the appropriate time to stop the sickness from spreading and assist farmers in raising production. The automatic identification and classification of plant diseases is another inescapable area that necessitates the creation of autonomous computer vision or computer vision systems using an image processing technique. For the objective of recognizing and classifying illnesses during the last several decades, a range of picture capture, augmentation, classification, and feature extraction technologies have been deployed.

Crop devastation is significantly influenced by pests. Because of pest-infested crops, agricultural yields are already declining, which has an impact on production rates. At this time, the idea of finding the plant disease in an unfavorable environment is dropped. The main obstacle is raising assembly rates and quality while lowering pesticide use in agricultural regions. Banana leaf diseases might be automatically categorized using an image segmentation method. Images are used to classify and identify illnesses in banana crops. Farmers may now evaluate the state of the plant effectively and economically thanks to this. To analyze and extract data from the pictures, segmentation is necessary. This image processing module makes it possible to conduct a more in-depth study by isolating the item of interest from the background. As a result, the performance of higher-level image analysis modules depends significantly on how well picture segmentation modules perform. For classification and segmentation, a hybrid fuzzy C-means technique is used.

Recurrent neural networks (RNN) and convolutional neural networks (CNN), both of which have shown their effectiveness in a number of disciplines, have lately helped to enhance the classification and detection of agricultural ailments. By combining RNN with CNN, a novel sequential picture classification model called the Gated-Recurrent Convolutional Neural Network is developed to identify illnesses (G-RecConNN). For farmers to recognize pest and disease infection and get the appropriate treatments, the identification and categorization of leaf diseases in the banana crop is a critical step. Banana fruit output is increased while saving time and money thanks to the invention of an automated method for identifying leaf diseases using image processing. To analyze the image and extract data from it for this automated process, picture segmentation is necessary. An crucial section of an image is removed during image segmentation, a fundamental step in image processing, to allow for further analysis.

With the right taxonomy, an automated system for tracking a plant's growth would be feasible. Forensic botanists, businesses, food engineers, and doctors may find this knowledge beneficial. To keep an eye on the plant and gather environmental information like humidity and temperature, it can integrate image processing with IoT. A plant recognition system has been created using images of the leaves of plants in the field of image processing. The detection model's input data may come from an in-field IoT sensor network in a banana plantation, and the output data may come from human record keeping and eye evaluation.

Effective pest management and control are the key components in the area of agricultural food safety. Therefore, accurate crop pest identification and automated monitoring have enormous practical utility throughout the agricultural planting process. Results for pest identification and detection have significantly improved over time with the development of deep learning-based algorithms. Although encouraging, these methods still fall short of the precision and efficacy required to detect agricultural pests in minute quantities. Future research on banana field pest identification may use these results as a reference. Governmental and non-governmental organizations may potentially utilize this information to create strategies for accelerating the finding of pests in banana crops. Our research questions' main subject areas are as follows:

- What is the most efficient way to find pests in a banana field?
- How much have insect populations in banana fields declined as a result of the use of contemporary technology?

According to the research questions, the following features of our study are highlighted:

- A detailed examination of pest detection in banana fields.
- A statistical analysis of insect sightings in banana crops.

Materials and methods

This systematic review is performed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Selçuk, 2019) The main objective of this study is to identify, differentiate and examine different methodologies involved in pest control of a banana field using image processing. This section describes the strategy involved in searching, selecting, and obtaining the required data for this systematic literature review. The objective of performing a systematic literature review is to differentiate, assess and examine previously performed related researches that are important to the objectives of the current research. This section describes the methods followed in selecting, accessing and extracting the data required for this systematic literature review.

Search Strategy: An electronic search was performed on publicly available databases such as IEEE Xplore, PubMed, Science Direct, and Google scholar using terms that focused on the scope of this study. Peer-reviewed papers from conference and journals that applied different machine learning algorithms for pest detection in banana field were selected and screened. The search was performed using the following keywords:“Pest Control System”, “Image processing”, and “Banana Pest”. Boolean operator ‘AND’ was used to search the databases.

Inclusion/exclusion criteria: Following inclusion and exclusion criteria were defined upon retrieving the studies to collect relevant information.

Inclusion Criteria:

- Research papers published in conferences and journals and are peer reviewed original articles.
- Research papers that have proposed machine learning approach for pest detection in banana field.
- Research papers with machine learning parameters such as classifier and accuracy.
- Research papers between the timeframe of 2000-2022.
- Research papers in English language.

Exclusion criteria:

- Research papers published in any other languages except English.
- Patents, Letters, editorials, unpublished studies, case reports, small case series, and cross-sectional studies
- Research papers published before 2000.
- Research papers that include any other plant/leaf except Banana field.
- Research papers that did not use a machine language approach for pest detection.

Results

The electronic search returned 104 articles. After removing the duplicates, 56 research articles remained, however 22 of them were dropped after title and abstract checks since they omitted to mention insect detection in banana fields. The remaining 22 articles were thereafter submitted to in-depth analyses during which each individual research article's component parts were meticulously scrutinized. The systematic review's inclusion of 22 pertinent research publications was then decided. Table 1 provides a summary of the selected studies' publication years, method used, and extent of pest detection in banana fields

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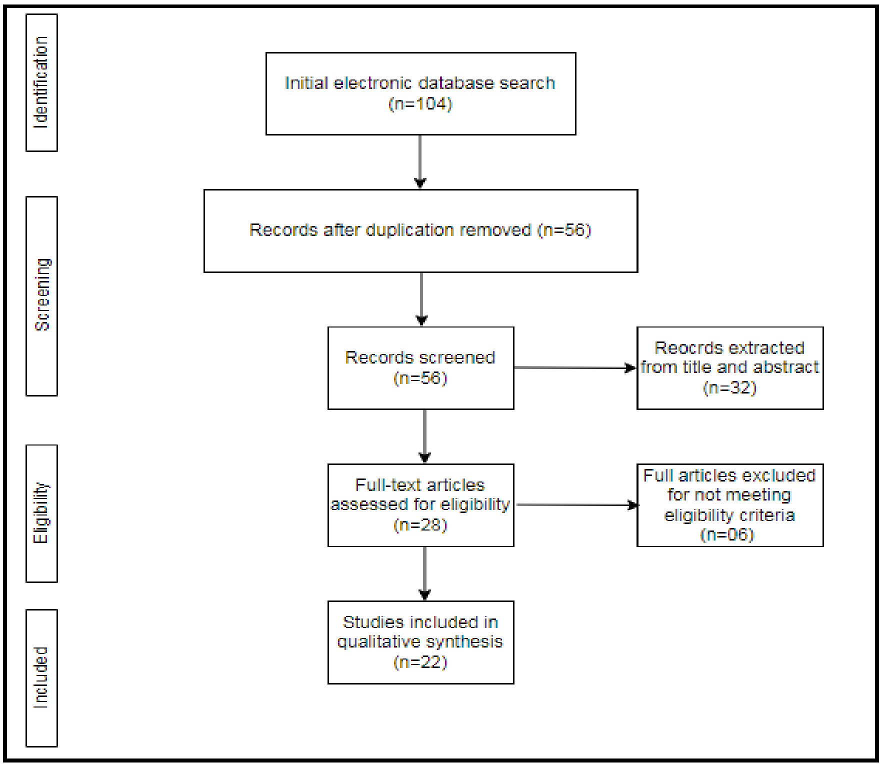

Figure 3: Study identification PRISMA flowchart

Table 1: 22 research papers for systematic review

Year	Authors	Method Used	Effectiveness	Future work
2017	Jihen et al.	Deep Learning-based Approach (LeNet architecture as a convolutional neural network)	Model started to stabilize from iteration 25 and achieved good accuracy at the final iteration	Test more banana and plants diseases with the model
2019	Selvaraj et al.	AI-powered detection (ResNet50, InceptionV2 and MobileNetV1)	Significant high success rate makes the model a useful early disease and pest detection tool	Develop a fully automated mobile app to help millions of banana farmers in developing countries
2020	Mary et al.	Develop a fully automated mobile app to help millions of banana farmers in developing countries	Highest classification accuracy of 99.35% for real data sets	Testing for other plant diseased image classification
2022	Narayanan et al.	Hybrid Convolutional Neural Network	Proposed technique shows 99% of accuracy that is compared with the related deep learning techniques	Mobile application can be created for the farmers to instantly identify the disease
2016	Tigadi & Sharma	Image Processing	Accurate images acquisition, pre-processing, feature extraction, and feature file creation	Replace the manual method for recognizing the diseases
2018	Kumar et al.	Image processing and Artificial neural network	100% accurate MATLAB results	Recognition system can replace the manual method for recognizing the diseases
2020	Selvaraj et al.	Aerial images and machine learning modelling method	Random forest based ML model classifies banana with more than 90% accuracy	Full-fledge AI-Powered disease surveillance system
2021	Aeberli et al.	AI-Powered disease surveillance system	Convolutional Neural Network (CNN) returns the highest plant detection accuracies	Precision agricultural applications to monitor health
2020	Bhamare & Kulkarni	Image Processing Techniques (ANN and RBG imaging)	Using image analysis to calculate the percentage of infected area accurately	Idea about the growth of pests and also its life stage
2021	Anasta et al.	Image processing based thermal camera (PCA statistical analysis)	Parameter values above 80%, namely the recall value of 85.4%, the Precision of 89.35%, the F measure of 87.33%, and the accuracy of 92.8%	Determine the speed at which the disease is spreading
2014	Johansen et al.	High Spatial Resolution Orthophotos	User’s mapping accuracy of 88% (n = 146) was achieved	Inspection rate of Banana Bunchy Top Virus
2021	Salokhe & Takmare	Wireless Sensor Network and Machine Learning	Accuracy of 58% for disease prediction	Increase the accuracy of the system for prediction of disease to 67%
2020	Ye et al.	UAV Remote Sensing	The fitting overall accuracies of the models were greater than 80%	Guidance for detecting the disease and crop planting adjustment
2021	Chaudhari & Patil	Deep Learning Technique	90.3% overall accuracy	Detection of disease in plants
2014	Prabha & Kumar	Image Processing Methods	Algorithms used for disease identification based on image processing approach were very accurate.	Pattern classification for better disease classification

2020	Almeyda et al.	Machine Learning Modelling (Logistic Regression)	The model developed can predict pest incidence at 79% accuracy	Improving the pest management of crops
2017	Lakshmi & Gayathri	IoT with Image processing (MATLAB)	Highly scalable image processing	Pattern recognition of leaf
2020	Deenan et al.	Image Segmentation Algorithms	Peak signal-to-noise ratio (PSNR) value (6608) and higher Server-Side Image Map (SSIM) value (0.196) than all other methods	Segmentation of banana leaf disease images
2022	Jayanthi et al.	Deep Neural Networks	YOLOv3 provides 92.11% accuracy when compared to Convolutional Neural Network (CNN) during pest detection	Region suggestion network for insect pest detection
2022	Krishnan et al.	Segmentation and classification model	Fast segmentation and classification	Better disease prediction
2022	Nandhini et al.	Deep Learning model of sequential image classifier	Convolutional Neural Network (CNN) catches potential features from the images in the sequences quickly	Early detection of banana tree disease
2021	Wang et al.	Sampling-balanced region proposal network	Adaptive RoI selection method for accurate localization and classification	Significant improvement in detection

Characteristics of research

22 papers were selected for this systematic review. Four of the studies focus on deep learning technique, Eight studies focus on image classification namely (Alex & Kanavalli, 2019; Almeyda, Paiva, & Ipanaqué, 2020; Anasta, Setyawan, & Fitriawan, 2021; Bhamare & Kulkarni, 2013; Deenan, Janakiraman, & Nagachandrabose, 2020; Kumar, Gokulpriya, Subharatha, & Dineash, 2018; Lakshmi & Gayathri, 2017; Narayanan *et al.*, 2022; Prabha & Kumar, 2014; Selvaraj *et al.*, 2020), The rest of the papers focus on either review of other papers or stand-alone techniques. The figure below is the pie chart representing the used dataset fractions. It depicts that image classification and review techniques have the highest and equal percentage of publications followed by deep learning techniques and then machine learning.

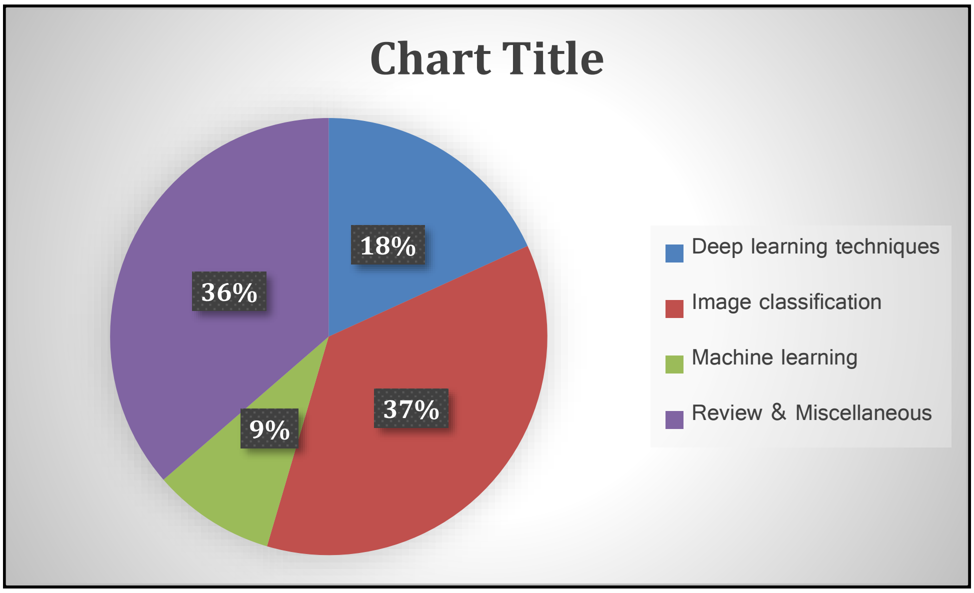

Figure 4: Pie chart for the used dataset (n=22)

Comparative Result Analysis: In order to confirm the efficacy of the proposed method, (Amara, Bouaziz, & Algergawy, 2017)have put up a series of studies using an actual dataset of banana disease data that was collected from the PlantVillage project. As part of the third plant village program, many images of both healthy and injured agricultural plants are available online. On the images in our dataset, three different categories—healthy, black sigatoka, and black speckle—are labeled. These images were captured in a range of backgrounds, lighting conditions, locations, scales, and orientations.

Numerous hotspots in Southern India and Africa were used to collect large datasets of photos of banana pest and disease symptoms and damage that had been successfully prescreened. (Selvaraj *et al.*, 2019) used a transfer learning approach to retrain three distinct deep neural network architectures and create a detection algorithm. Using photos captured at various locations across the banana plant, six distinct models were created from a total of 18 multiple categories. In their investigation, ResNet50 and InceptionV2 models performed better than MobileNetV1 models. With an efficiency of more than 90 percent in the majority of the examined models, these models take into account the most recent findings in banana disease and pest detection. These experiment results are on par with other cutting-edge models that have been discussed in the literature. They assessed the SSD MobileNetV1's efficiency in order to employ these detecting abilities on a mobile device in the future. To assess the efficacy of different models in automated sickness detection technologies, efficiency and verification measures were also established.

The Y element of the YCbCr input picture is taken into account during fragmentation in (Singh & Athisayamani, 2020). It is the end result of an unbalanced addition of the RGB and B components of a gamma-compressed color picture. In a color picture, it indicates brightness. When contrasted to an RGB picture, the Y color element for banana leaf diseases yields satisfactory findings. These findings demonstrate that the suggested framework employs a more effective and simple categorization technique. This less complicated classification framework produces superior results when used to categorize photos of banana leaf disease in compared to other current classification frameworks.

By using Python programming in the Jupyter notebook setting with an I5 CPU, 32 GB of RAM, and 6 GB AMD GPUs from NVIDIA, the detection and categorization of banana tree ailments were evaluated. The study in (Narayanan *et al.*, 2022) used 5 different kinds of acquired photographs to show the suggested way of classifying pictures. The suggested CNN, whose design is based on LeNet-5, is used by the proposed model to collect the picture data and obtain the image attributes. The first-level P1 binary SVM then categorizes the picture as either an infected leaves or a healthy leaf using the attributes identified by the fusion-based SVM testing approach. When a fresh picture is offered as a search query and the classification decides on its own in phase P1 if the given test image is a real image, the procedure is complete.

It is crucial to choose the kind of networking, the training strategy, the number of hidden neurons, and other ideal qualities before supplying the neural network with the data. Use a feed-forward backpropagation algorithm (Narayanan *et al.*, 2022). Based on the afflicted pixel area, grades are used to represent the problem's severity. Before choosing the query picture for testing, the dataset file, which contains a variety of photos needed for testing, is first generated.

Feature extraction, a kind of responsibility reduction, efficiently communicates the essential elements of an image that are essential for classifying sickness**.** (Oerke et al.,2026) selected the features in this example based on statistical considerations. Using the statistical moments of the image's grey level histogram is one of the simplest approaches to portray texture. This feature is based on the distribution of run length and edge frequency, the grey level histogram, and the grey level cooccurrence matrix. We have focused just on first and second order statistics, or features based on co-occurrence and grey level.

The findings demonstrate that the (Selvaraj *et al.*, 2020) model can correctly identify 74 percent of the test set. To distinguish between true positives (TPs) and false positives, they extracted the reliability and recollection data using IoU. (FPs). This work is essential when the illness classifier considers expectations. The computer may have also recognized the unlabeled forecasts as datasets and ultimately earned high FPs since it is exceedingly difficult to label every single and group of bananas in the orthomosaics. This answers why in both the training and testing, FPs are found to be greater than TPs.

(Selvaraj *et al.*, 2020) demonstrate that the shape of adjacent crowns had an effect on CNN identification when there was significant crown overlap resulting from different orientations or situations. It was shown that false negative detection methods often occur in areas with dense vegetation, despite CNN having a lower median crown misinformation positive than the other methodologies. The crown distribution of plants grown does not necessarily represent the degree of crown overlapping since nearby plants may have had large crowns that encroached on the excluded plant or instances of double crown plants that grow from the same corm.

A technique for image segmentation called background subtraction aims to discern between stationary and moving or changing objects in a photograph. In (Bhamare & Kulkarni, 2013), frame differencing is used for the most straightforward operations, while statistical approaches are used for the most challenging ones. Simple frame differencing, for instance, would make a leaf from a moving tree seem in the front, while a good statistical technique would make the leaf appear in the background since it is always there and essentially never moves.

One may assess the effectiveness of the suggested technique by taking into account the values of Retention, Accuracy, F-Measure, and Reliability. The (Anasta *et al.*, 2021) method is considered to be very effective if both memory and accuracy scores are more than 60%. The thermal image processing output is compared to the original image in order to identify the positive overall, false negatives, true positive, and genuine negative values.

After the 1 km 1 km orthophoto tiles were divided into four groups for batch processing in the eCognition Server software, each picture tile in (Anasta *et al.*, 2021) took between 15 and 20 minutes to process. Individual banana plants were sometimes missed, but clusters of banana plants were often recognized and precisely described using the constructed rule set. In contrast to those that were instantly identifiable, those with stronger contrast or those that visibly projected shadows in the form of leaves on the ground were often ignored.

The Kolhapur region of the Maharashtra state, where banana growing is prevalent in certain regions, will be the site of this experiment. (Alex & Kanavalli, 2019) selected the rainy season on purpose since it is the time of year when the illness is most likely to spread over the banana crop. At this time of year, precipitation, abrupt temperature changes, and relative humidity are the main causes of illness and insect infestation. The disease alarm system regularly checks if the threshold criteria have been satisfied before notifying the farmer. Compared to the conventional open-eye evaluation by farmers in the field, our technique produces more accurate results. More quickly than with the conventional technique, the cumulative count barrier is being broken. This makes sense considering that the system is used in the field 24 hours a day, 7 days a week, making it difficult for the farmer to directly see it.

VD1 from the Guangxi site and VD2 from the Hainan site were used to confirm the Fusarium wilt detection method in (Ye *et al.*, 2020). The validation results at two locations showed that CIRE and CIgreen had excellent performances for detecting Fusarium wilt, with OAs both over 70% and Kappa values all above 0.4. This illustrates the adaptability of the Fusarium wilt detection method in a variety of environmental settings. This suggests that if the Fusarium wilt detection approach were to be used in other situations, some degree of dependability would be lost. These elements could be to blame for this circumstance. The various species present at the two testing locations can be one of the most crucial factors determining the verification's outcomes. The types employed for VD1 and VD2 were Williams B6 and Baxijiao, respectively. The two varieties had different biophysical and biological characteristics. The spectral information may alter depending on how these variety features vary. Second, the development phases at each of the two experimental locations differed significantly due to the unique planting methods utilized there. Each of the two trials used in this investigation was at a distinct stage of development when photos were obtained.

The approach presently uses a banana leaf picture as the input, expands the image during preprocessing, and then applies thresholding and contour masking to collect data. The image's characteristics are then retrieved using CNN. As a result, the characteristics of the input image are identified, and the image is then categorised using these characteristics. Because they are more accurate at recognizing diseases as in Ye,, support vector machines are among the finest supervised learning algorithms used in automated sickness diagnosis.

The first step in converting the returned illness picture into a higher-dimensional space is choosing a nonlinear function. The mapping and classification processes are made easier by the creation of a hyperplane or group of hyperplanes in (Prabha & Kumar, 2014). The functional margin is the separation between the hyperplane and the closest data point. Diseases' higher value results in a lower classification mistake when they are automatically detected.

In each iteration, the ML models' parameters were fitted. (Almeyda *et al.*, 2020) looked for each model's best classifiers. They were aware that they needed to choose models whose performance metrics were around 0.7. The accuracy of the SVM model was found to be 78 and 79 percent in the training set and testing set, respectively. The LR model, on the other hand, obtained 79 and 64% in the same manner. The SVM model performs best at predicting when pests will develop in banana crops. Compared to other machine learning techniques, it methodology produces superior results.

With the right taxonomy, it could be feasible to automate the process of tracking a plant's growth. Forensic botanists, businesses, food engineers, and medical specialists could find this material beneficial. To monitor the plant and gather environmental data like humidity and temperature, (Lakshmi & Gayathri, 2017) blends image processing with the internet of things. Thanks to an identification method for identifying plants using images of their leaves created in image processing, the use of pesticides may be managed with the use of photographs. Before a pattern matcher compares the data from this picture with those in the database to find potential matches, the system pre-processes and extracts characteristics from the image. Color, texture, and form are just a few of the several leaf characteristics that are retrieved and contrasted.

Using MSE, PSNR, and SSIM indices on pictures of leaves, several segmentation algorithms are contrasted, and their efficacy is assessed. According to the findings, the geodesic approach is the most effective technique for accurately segmenting the disease-infected zone, where its MSE was much lower and its PSNR and SSIM were better. Multiple thresholding is the second-best strategy. The geodesic approach outperformed earlier tactics because to its greater SSIM, PSNR, and MSE values, which demonstrate reduced volatility. As a result, it is possible to see the geodesic method to segmentation in (Deenan *et al.*, 2020) as a preprocessing phase in the creation of an automated system to extract the necessary area of interest from the picture.

Look into the predicted plant illness at the wrong time, (Jayanthi, Priyanka, Shalini, & Grace, 2022). New methods for identifying and detecting insect pests have been developed despite the drawbacks of the conventional convolution neural network (CNN)-based approach. For CNN-based algorithms to optimize different parameters, a large dataset is needed. According to CNN, a two-stage method is suggested for identifying and detecting insect infestations. This project also includes an area recommendation network for YOLOv3-based re-identification and insect pest monitoring. A knowledge augmentation technique based on image processing is suggested to train these models. When compared to CNN, YOLOv3 has a bug recognition accuracy of 92.11 percent.

(Krishnan, Deepa, Rao, Divya, & Kaviarasan, 2022) describes an image segmentation technique for diagnosing diseases that harm banana leaves automatically. Images are used to categorize and identify infected banana crops. Farmers may now evaluate the state of the plant effectively and economically thanks to this. To evaluate and extract data from the pictures, segmentation is necessary. This image processing module makes it possible to conduct a more in-depth study by isolating the item of interest from the background. As a consequence, the effectiveness of picture segmentation modules has a considerable impact on the success of higher-level image processing modules. A hybrid fuzzy C-means algorithm is utilized for segmentation and classification. The properties of color, shape, and texture were also scrutinized in order to detect diseases in banana plants.

Recurrent neural networks (RNN) and convolutional neural networks (CNN), both of which have shown their effectiveness in a number of disciplines, have recently made improvements in the classification and detection of agricultural ailments. (Nandhini, Kala, Thangadarshini, & Verma, 2022) seeks to assist plantain growers by using a Deep Learning Model for disease categorization and early prediction. By combining RNN with CNN, a novel sequential picture classification model called the Gated-Recurrent Convolutional Neural Network is developed to identify illnesses (G-RecConNN). The plant picture sequences provide the model with data. The most current data utilized in the study came from

Tamil Nadu, a state in southern India. This approach aims for a number of benefits, such as improvements with fewer real data points, simple online performance assessment, less data pre-processing, etc. In farmer assistance programs that analyze continuous pictures of banana plants in whole or in part for the early identification of banana tree illnesses, the G-RecConNN model was used as a consequence of the experimental findings.

With the advancement of deep learning-based algorithms, results for pest identification and detection have considerably improved over time. Although promising, these techniques currently lack the accuracy and effectiveness needed to find agricultural pests in small amounts. Since existing deep learning-based techniques may not be capable of extracting enough different visual information for small things in a photo, it is challenging to build a classifier to differentiate and classify minute pest items from surroundings or other similar objects. Conversely, in order to solve the problem of tiny insect detection and recognition, (Wang *et al.*, 2021) tries to recast the current area proposal network and conduct further study at different sizes for quick identification of micro pests. In order to create a deeper representation of pest features, especially the intricate parts of tiny item pests, they start by introducing focus mechanisms into the Residual network, which was influenced by the visual attention network. Then, it is suggested to use a sampling-balanced region proposal generation in order to improve the RPN's ability to identify pests and to deliver more high-quality item suggestions. Customers may now learn images from multiple feature pyramid levels owing to a special adaptive region of interest (RoI) choice mechanism they created. With a mean recall of 89.0 percent and mAP of 78.7 percent in tests on the predicted AgriPest21 dataset, the method surpasses state-of-the-art methods including SSD. The figure below shows the trend of publications since 2014. It shows that most publications for review were chosen from 2020 because that was the peak time for banana infestation. To validate the review findings no papers older than 2014 were chosen.

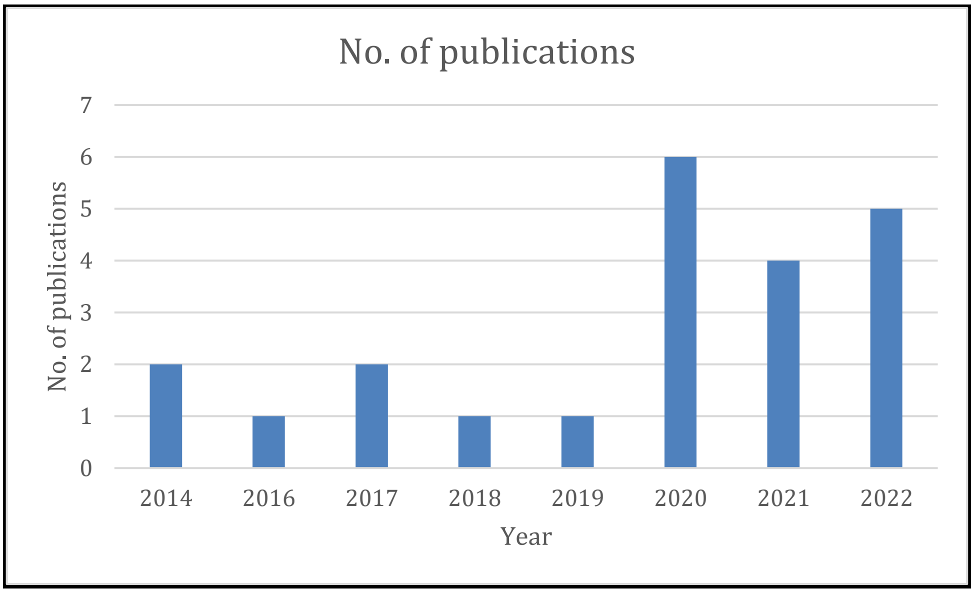

Figure 5: The trend of publications since 2014

DISCUSSION

Plant diseases are a major problem in agriculture because they reduce crop quality and yield. The progress and standard of living in underdeveloped countries are significantly harmed by the absence of diagnostic instruments. The development of low-cost, user-friendly devices for early plant disease detection is crucial. (Amara *et al.*, 2017) proposed a convolution neural network-based technique for recognizing and classifying banana diseases. To assist farmers in locating the illness in the banana plant, the suggested model may be used as a decision support system. As a result, the farmer may photograph a leaf displaying symptoms, and the algorithm will subsequently be able to recognize the disease. Their main contribution is the application of deep learning models to differentiate between the two well-known banana disorders, banana sigatoka and banana speckle, in difficult real-world situations and illumination circumstances, as well as modifying image size, quality, attitude, and direction. This algorithm was able to provide precise classification results after prolonged testing. It has been shown that using the recommended technique may significantly and successfully help in the accurate diagnosis of leaf diseases.

A thorough study of real-time pest and disease detection is still lacking, notwithstanding the many computers imagined methods for automated crop detection of diseases and categorization that have been created. In order to easily identify signs of banana pests and pathogens on various areas of the banana trees using real-time field images, a novel application of the deep transfer learning approach was examined in (Selvaraj *et al.*, 2019). This technique offers a realistic and feasible answer for identifying the kind and development of illnesses in banana plants, which is a fundamental contrast between it and other ways to categorizing plant diseases. For a variety of banana illnesses, the developed model was able to distinguish between normal and sick plant portions. The development of a control system that will aid in the early detection and control of illnesses and pests will be made easier by the use of the reliable performance from this research.

The productivity and quality of the crop are decreased by diseases that harm banana leaves. Their growth and quality of life are also significantly impacted by the lack of diagnostic tools. As a result, it's critical to find banana leaf infections as soon as feasible. (Singh & Athisayamani, 2020) claims that heap auto encoders (HAEs), a ground-breaking deep learning strategy, have been proposed. The recommended method reduces the need for unique quality while enabling efficient extraction of critical traits. HAE also uses the Rectified Linear Units (ReLU) activation function and the dropout approach. The effectiveness of the small training set is improved, and the training method's overfitting difficulties is reduced. Farmers are advised to use this strategy as a decision-support tool to assist them in identifying the sickness in a banana leaf. Therefore, the farmer may photograph a banana leaf displaying the symptoms, and the algorithm would identify the illness kind from there. The recommended strategy stands out due to its exceptional resilience, effectiveness, and practicability. The results of the recommended approach demonstrate that it outperforms other tried-and-true techniques. This framework offers the highest classification accuracy for real data sets, at 99.35 percent.

Both the production of food for people and the growth of the national economy are significantly influenced by agriculture. Therefore, it is essential to treat agricultural products correctly. It is essential to preserve bananas free of harmful illnesses like BBTV, BXW, BFW, and banana black Sigatoka since they are a crop that is grown all over the globe and are of the highest significance (BBS). By examining not only the banana leaves but also other sections of the crop using CNN and an FSVM, which is a mix of binaries and classification SVM, a detailed deep learning-based technique for identifying and diagnosing the banana sickness has been described in (Narayanan *et al.*, 2022). The suggested approach is highly precise and F1-score together with an accelerated performance of 99 percent overall accuracy, making it the most effective for identifying diseased banana trees. The manual method of detecting banana plant disease may be replaced by the automated method in (Narayanan *et al.*, 2022). Since it is more accurate than the human method, farmers or plant pathologists will find it highly helpful to detect the illness and its possible therapies. This tactic will result in increased crop production.

A technique for tall banana plant disease detection was developed using the MATLAB computer in (Kumar *et al.*, 2018). Image capture, pre-processing, segmentation, feature extraction, and feature file output are all parts of the system's development. A variety of criteria are selected, computed, and employed for ANN-based sickness categorization during the feature extraction step. The automated technology may take the place of the manual method for tall banana plant disease detection. Since it is more accurate than the manual method, farmers or plant pathologists will find it highly useful in spotting the illness and its remedies. This plan will increase agricultural output and raise the quality of food.

The combination of pixel-based banana categorization with a randomized forest (RF) model using integrated features of vegetal indices (VIs) and principal component was shown in (Selvaraj *et al.*, 2020) as a promising strategy for mapping bananas under mixed-complex African environments (PCA). This study shows that high quality sensors deliver more precise mapping of bananas than medium-quality satellite images (S2). Effective banana mapping with open-source resolution satellite in mixed complex systems is still difficult, despite improvements in the synthesis of data from various sensor inputs. Using UAV-based RGB vision technologies, they were able to spot bananas and their main diseases with more accuracy and fewer errors. The practical, affordable UAV-RGB based mixed-model illness identification pipeline utilized in this work may be able to classify other agro-diseases. The mixed-model pipeline-based approach developed from this study may be strengthened even more by retraining the CNN model with a wider dataset that covers a range of crops and diseases, which will be the subject of the future work. They want to collect new real-world data from our global banana collaborators in Central America, Africa, and Asia in order to improve the existing datasets and assess the developed ML algorithms. The results of this research are being incorporated into other banana communicable disease platforms operated by the CGIAR Research Group on Seeds, Root vegetables, and Bananas to enhance the digital illness surveillance system globally.

The mapping of individual banana plants is a crucial step in acquiring precise measurements and important information on plant development, status, and health due to the distinctive way that banana plants develop as well as their unique physical and developmental characteristics. Our knowledge of crop dynamics, including phenology, yield forecast, and the planning of maintenance operations, is greatly improved by the use of multi-temporal picture captures. In order to compare the performance of three distinct methods for finding banana crowns in a GEOBIA scenario, multispectral UAV footage was obtained over a period of days in (Selvaraj *et al.*, 2020). CNN was shown to be the program most suited for identifying banana plants, as opposed to TM and LMF. When utilized on data from different dates, the CNN models generated great results, but they may be strengthened by precisely identifying objects using contextual and crown elevation data (CHM) (CHM). By comparing measurements of plant morphology received from UAVs with measurements collected in the field, it could be feasible to identify characteristics of those plants that the three categorization methods missed. The CNN approach was effectively employed to meet the stated goals within the restrictions of the research, according to these findings. The CNN approach also provides significant information that will be helpful in formulating workable processes, broadening the range of feasible applications, and investigating crop management applications.

(Bhamare & Kulkarni, 2013) can determine the proportion of the contaminated region using picture analysis. Pixels are used to display the result. Banana tree infections are one of the issues confronted by agricultural professionals from all over the globe who are fighting against bioagressors. A big part of it involves image processing technology. In order to prepare for future work, our initial goal is to locate black sigatoka on banana trees and other bioaggressors or plant illnesses.

A cognitive approach involves the addition of new items for recognition or the introduction of new image-processing techniques to extract the necessary data. They provide a novel technique for spotting pests on banana leaves early on. We used scanning image gathering, sample optimization, and cutting-edge cognitive vision to distinguish organic items on a complicated backdrop. It serves as an example of how several methods and disciplines may be combined to create a dependable, automated system. For fast identifying Black sigatoka, the prototype method was effective. It performs at a level that is equivalent to a traditional manual technique and is relatively easy to use. Instead, they seek to more precisely identify and quantify the starting points of bioagressor assaults in order to choose the best course of action.

(Anasta *et al.*, 2021) describes a method for use a thermal camera to find ill leaf areas on banana plants. The suggested method works well for locating disease-related spots on banana leaves. This is because the accuracy rate is 92.8%, the recall rate is 85.4%, the precision rate is 89.35%, and the FMeasure rate is 87.33%. Future observations will be required to gauge the disease's development and develop preventive strategies.

(Anasta *et al.*, 2021) concentrated on automatically detecting and classifying banana plants on the Sunshine Coast in Queensland, Australia, in order to make it easier to locate banana plants and raise the inspection rate for Banana Bunchy Top Virus. With a final visual phase to validate or deny the possibilities, a novel method of object-based image analysis was created to automatically find and classify possible banana plants. Accuracy rates for users and manufacturers were 88 and 79 percent, respectively. To distinguish between genuine banana plants and prospective banana plants, the visual interpretation stage took an average of 13 minutes each picture tile. Our method requires a fraction of the time of human photo interpretation, which typically takes 73 minutes per image tile. The developed rule set provides a new method for automatically creating buffers around features that may be used in other applications when just a portion of the feature can be mapped. This research expands our understanding of object-based image processing for optical image data with exceptionally high spatial resolution and its use in real-world scenarios. By prioritizing field inspections of banana plants for the detection of the Banana Bunchy Top Virus in the future, the developed mapping technique has the potential to considerably contribute to the identification of banana plants.

The wireless sensor network system presented in (Alex & Kanavalli, 2019) provides real-time farm temperature, relative humidity, and rainfall data, which are crucial indications for predicting agricultural weather conditions. Our machine learning technology will assist you create future predictions based on previously learned data. Making projections for the future also needs the utilization of prior data. Farmers benefit when this technology is really used to minimize crop loss, which also aids India in achieving sustainable agriculture, one of the issues the nation is now facing. In the future, they may conduct the experiment throughout a number of years and seasons. As a result, they will have a thorough grasp of diseases. For machine learning to be effective, the model must also be trained on a variety of datasets.

(Ye *et al.*, 2020) created a detection technique for banana Fusarium wilt using VIs generated from UAV-based multispectral data combined with BLR. The results demonstrated that Fusarium wilt in bananas may be recognized using this approach. Each of the NDVI, NDRE, CIRE, and CIgreen fits had an OA of more than 80%. The CIRE outperformed the other VIs under consideration for both verification datasets 1 and 2. When comparing VIs of the same kind, the red-edge band VIs outperformed the ones without one. According to the simulation of imaging at different spatial resolutions, Fusarium wilt could be differentiated with a high degree of accuracy when the resolution was more than 2 m. The accuracy of Fusarium wilt detection decreased with reduced resolution. The study's findings suggest that red-edged UAV-based remote sensing imagery is an effective tool for identifying the Fusarium wilt disease that affects bananas and may be used to guide adjustments in crop planting and disease management.

(Singh & Athisayamani, 2020) model that might serve as a decision-support tool and assist farmers in identifying the illness in banana plants. The suggested network model's goals are to identify and diagnose banana diseases. A banana leaf's health or infection may be determined using the instrument. Future research will focus on making diagnoses, improving the precision of identification and diagnosis. Using these deep learning algorithms, agricultural specialists might identify plant issues and then offer farmers remedies.

The automated detection and categorization of illnesses in banana leaves is more precise when image processing methods are used. These technologies have eliminated the need to locate subject-matter specialists who are skilled in diagnosing ailments. Time and money are saved in this way. The symptoms of many diseases that affect banana plant leaves are listed in (Prabha & Kumar, 2014). Research on algorithms for employing image processing to diagnose diseases is also ongoing. The necessity for pattern categorization for more accurate disease diagnosis is also addressed in this work.

According to (Almeyda *et al.*, 2020), organic banana plantations in Piura are expected to host the "Trips de la mancha roja" insect. In this work, they provide a prediction model to categorize pest information into categories with low and medium pest occurrence. Data on the frequency of pests and the weather were used as the model's inputs and outputs, respectively. The PCA approach was used to choose the top six attributes. Support vector machines and logistic regression were the two ML models created. The classification accuracy of 79 percent that the SVM model successfully generated is regarded as an acceptable level for this experimental project. LR models have a few advantages over other ML techniques, like being easy to build and using less computing power to train. The SVM model, on the other hand, has a solid mathematical foundation and can categorize things consistently and properly, as this study paper has shown. By giving them early notice of the insect's existence and prompt pest management measures, this strategy would help farmers in Piura make better decisions regarding their organic banana harvests. Farmers may be able to better manage their crops, make better use of the resources at their disposal, raise production, and improve banana quality by using the suggested measures in the future. The figure below shows the percentage accuracy of results for 10 publications. The paper by Kumar et al. showed 100% accuracy on MATLAB making it the most effective way of pest detection

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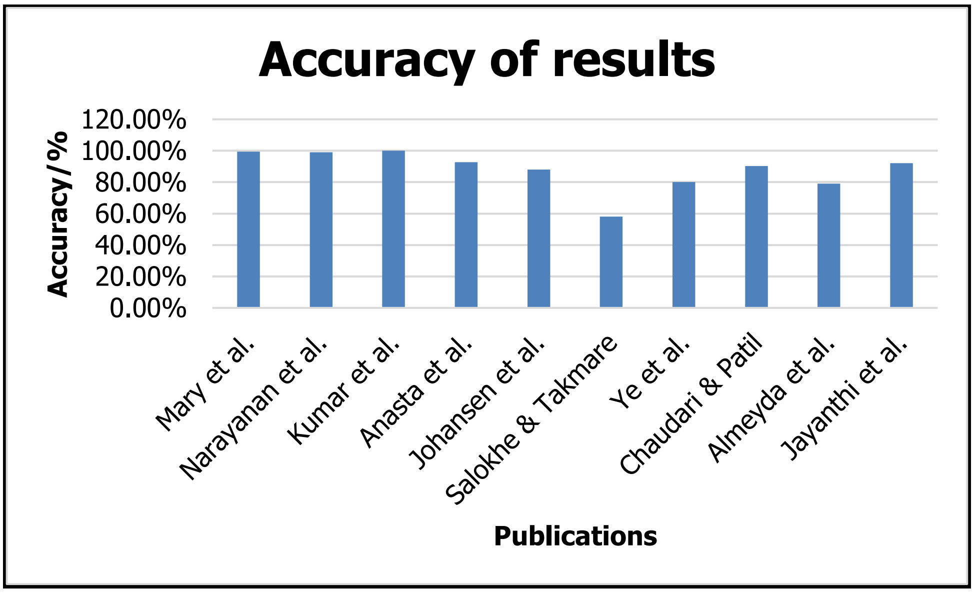

Figure 6: Percentage accuracy of 10 different publications

Conclusion

Since Banana is a staple food, pest detection in banana field is very important. 22 papers in this systematic review present viable and efficient techniques for the detection which can be classified as image classification, artificial intelligence and machine learning, deep learning, and mobile apps. All of these methods can assist in pest detection in banana field. To assist farmers in locating the illness in the banana plant, these suggested models may be used as a decision support tool. As a result, the farmer may photograph a leaf that has symptoms, and the system can subsequently recognize the disease. The key contribution of all these papers is the use of deep neural networks/image classification/machine learning to recognize the two well-known banana illnesses, banana sigatoka and banana speckle, under tough real-world settings and lighting circumstances, as well as altering image size, quality, posture, and orientation.

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References

Alex, S. A., & Kanavalli, A. Intelligent computational techniques for crops yield prediction and fertilizer management over big data environment. *International Journal of Innovative Technology and Exploring Engineering (IJITEE),* ***8***(12).(2019).

Almeyda, E., Paiva, J., & Ipanaqué, W.*Pest incidence prediction in organic banana crops with machine learning techniques.* Paper presented at the 2020 IEEE Engineering International Research Conference (EIRCON). (2020)

Amara, J., Bouaziz, B., & Algergawy, A. A deep learning-based approach for banana leaf diseases classification. *Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband*.(2017).

Anasta, N., Setyawan, F., & Fitriawan, H.*Disease detection in banana trees using an image processing-based thermal camera.* Paper presented at the IOP Conference Series: Earth and Environmental Science. (2021)

Bhamare, S. P., & Kulkarni, S. C. Detection of black Sigatoka on banana tree using image processing techniques. *IOSR Journal of Electronics and Communication Engineering*, 60-65.(2013).

Camargo, A., & Smith, J. An image-processing based algorithm to automatically identify plant disease visual symptoms. *Biosystems engineering,* ***102***(1), 9-21.(2009).

Deenan, S., Janakiraman, S., & Nagachandrabose, S. Image segmentation algorithms for Banana leaf disease diagnosis. *Journal of The Institution of Engineers (India): Series C,* ***101***, 807-820.(2020).

Jayanthi, B., Priyanka, T. A., Shalini, V. B., & Grace, R. K.*Pest Detection in Crops Using Deep Neural Networks.* Paper presented at the 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS). (2022)

Karmokar, B. C., Ullah, M. S., Siddiquee, M. K., & Alam, K. M. R. Tea leaf diseases recognition using neural network ensemble. *International Journal of Computer Applications,* ***114***(17).(2015).

Kobayashi, T., Kanda, E., Kitada, K., Ishiguro, K., & Torigoe, Y. Detection of rice panicle blast with multispectral radiometer and the potential of using airborne multispectral scanners. *Phytopathology,* ***91***(3), 316-323.(2001).

Krishnan, V. G., Deepa, J., Rao, P. V., Divya, V., & Kaviarasan, S. An automated segmentation and classification model for banana leaf disease detection. *Journal of Applied Biology and Biotechnology,* ***10***(1), 213-220.(2022).

Kumar, V., Gokulpriya, D., Subharatha, R., & Dineash, V. Banana tall plant disease detection and classification using image processing and artificial neural network. *International Journal of Advanced Science and Engineering Research,* ***3***(1), 452-459.(2018).

Lakshmi, K., & Gayathri, S. Implementation of IoT with image processing in plant growth monitoring system. *Journal of Scientific and Innovative Research,* ***6***(2), 80-83.(2017).

Nandhini, M., Kala, K., Thangadarshini, M., & Verma, S. M. Deep Learning model of sequential image classifier for crop disease detection in plantain tree cultivation. *Computers and Electronics in Agriculture,* ***197***, 106915.(2022).

Narayanan, K. L., Krishnan, R. S., Robinson, Y. H., Julie, E. G., Vimal, S., Saravanan, V., & Kaliappan, M. Banana plant disease classification using hybrid convolutional neural network. *Computational Intelligence and Neuroscience,* ***2022***. (2022).

Oerke, E.-C. Crop losses to pests. *The Journal of Agricultural Science,* ***144***(1), 31-43.(2 Begum Nusrat Bhutto Women University, Department of Information & Communication Technologies, Sukkur, 006).

Peña, J. M., Gutiérrez, P. A., Hervás-Martínez, C., Six, J., Plant, R. E., & López-Granados, F. Object-based image classification of summer crops with machine learning methods. *Remote sensing,* ***6***(6), 5019-5041.(2014).

Prabha, D. S., & Kumar, J. S. Study on banana leaf disease identification using image processing methods. *Int. J. Res. Comput. Sci. Inf. Technol,* ***2***(2), 2319-5010. (2014).

Saleem, M. H., Potgieter, J., & Arif, K. M. Plant disease detection and classification by deep learning. *Plants,* ***8***(11), 468.(2019).

Selçuk, A. A. A guide for systematic reviews: PRISMA. *Turkish archives of otorhinolaryngology,* ***57***(1), 57. (2019).

Selvaraj, M. G., Vergara, A., Montenegro, F., Ruiz, H. A., Safari, N., Raymaekers, D., . . . Omondi, A. B. Detection of banana plants and their major diseases through aerial images and machine learning methods: A case study in DR Congo and Republic of Benin. *ISPRS Journal of Photogrammetry and Remote Sensing,* ***169***, 110-124.(2020).

Selvaraj, M. G., Vergara, A., Ruiz, H., Safari, N., Elayabalan, S., Ocimati, W., & Blomme, G. AI-powered banana diseases and pest detection. *Plant methods,* ***15***, 1-11.(2019).

Singh, R., & Athisayamani, S. Banana leaf diseased image classification using novel HEAP auto encoder (HAE) deep learning. *Multimedia Tools and Applications,* ***79***(41-42), 30601-30613.(2020).

Swarupa, V., Ravishankar, K., & Rekha, A. Plant defense response against Fusarium oxysporum and strategies to develop tolerant genotypes in banana. *Planta,* ***239***, 735-751.(2014).

Triwidodo, H., Tondok, E. T., & Shiami, D. A. Pengaruh Varietas dan Umur Tanaman Berbeda terhadap Jumlah Populasi dan Tingkat Serangan Hama dan Penyakit Pisang (Musa sp.) di Kabupaten Sukabumi. *Agrikultura,* ***31***(2), 68-75.(2020).

Uwamahoro, F., Berlin, A., Bylund, H., Bucagu, C., & Yuen, J. Management strategies for banana Xanthomonas wilt in Rwanda include mixing indigenous and improved cultivars. *Agronomy for Sustainable Development,* ***39***, 1-11.(2019).

Wang, R., Jiao, L., Xie, C., Chen, P., Du, J., & Li, R. S-RPN: Sampling-balanced region proposal network for small crop pest detection. *Computers and Electronics in Agriculture,* ***187***, 106290.(2021).

Ye, H., Huang, W., Huang, S., Cui, B., Dong, Y., Guo, A., . . . Jin, Y. Recognition of banana fusarium wilt based on UAV remote sensing. *Remote sensing,* ***12***(6), 938.(2020).