Utilizing Aerial Imagery and Deep Learning Techniques for Identifying Banana Plants Diseases

Mohd Aliff[1*], *Muhammad* Luqman[1], *Mohd Ismail* Yusof[1], *Nor Samsiah* Sani[2], *Mohd Usairy* Syafiq[1], *Siti Fairuz Nurr* Sadikan[3], *Hafizah* Mahmud[4]

[1]Quality Engineering Research Cluster, Malaysian Institute of Industrial Technology, Universiti Kuala Lumpur, 81700, Johor, Malaysia
[2]Center for Artificial Intelligence Technology, Universiti Kebangsaan Malaysia, Selangor, Malaysia
[3]Faculty of Plantation and Agrotechnology, Universiti Teknologi MARA (UiTM), Cawangan Melaka Kampus Jasin, 77300 Merlimau, Melaka, Malaysia
[4]UTM-MPRC Institute for Oil & Gas (IFOG), Universiti Teknologi Malaysia, Malaysia

Abstract. The primary agricultural pursuit in Malaysia centres around banana cultivation; however, this vital crop faces the daunting challenge of multiple diseases that hinder its growth. The adverse consequences of these diseases extend beyond the farms to impact the nation's economy. To empower farmers with the tools to promptly identify and categorize these diseases, image processing techniques offer a valuable solution. This research leverages deep learning Convolutional Neural Networks (CNN) implemented through MATLAB in conjunction with a DJI drone. By harnessing this technology, the system can automatically detect and classify major banana diseases. The study meticulously fine-tuned several hyperparameters to achieve impressive training and testing accuracy levels. The results revealed that the model attained its highest training accuracy of 81.27% at epoch 8 and its lowest accuracy of 78.40% at epoch 4, demonstrating its potential to aid in early disease detection and classification in banana crops.

1 Introduction

In the era of Industry 4.0, technological advancements have permeated diverse sectors, revolutionized traditional practices, and unlocked unprecedented potentials [1-3]. In agriculture, the convergence of cutting-edge technologies such as microcontroller, the Internet of Things (IoT), Robotics, and Deep Learning has ushered in a new paradigm of smart farming [4, 5]. This integration holds immense promise for optimizing agricultural processes, increasing productivity, and ensuring sustainable resource management. These transformative technologies play a pivotal role in reshaping the agricultural landscape, offering innovative solutions to address contemporary challenges [6, 7]. These papers delve into the multifaceted applications of Industry 4.0 technologies in agriculture, exploring their synergistic effects and impact on farming practices for a more resilient and technologically empowered agricultural future [8, 9].

The agricultural sector plays a crucial role in maintaining a healthy ecosystem. Plant disease is a common occurrence in the agricultural sector, making accurate identification of plant ailments essential. In today's environment, the prevalence of plant diseases has decreased significantly because of the damage they do to productivity. Polyphenols, found in both green tea and banana leaves, are powerful natural antioxidants. Due to environmental conditions, several fungal and bacterial infections affect the plants, which will in turn diminish the production. Reduced crop yields can be traced back to a lack of understanding in fertilizer management, an absence of awareness about diseases and pests, and an absence of available experts at the farming field [10]. But currently, thanks to research efforts, there is a significant increase in the output of disease-free banana leaves [11]. In this paper, many prevalent diseases of banana leaves, leafspot and sigatoka are classified using machine learning and deep learning techniques.

Automated plant disease identification and classification is an essential subfield in computer vision and machine vision research, which uses image processing techniques. Early detection is very important in these fields for ensuring consistent quality of output. New methods, including those based on Computer Vision and AI, have been proposed in recent studies as a means of early detection. To create a computational simulation of human biochemical processes using criterion theory, Deep Learning (DL) should be a subclass of Machine Learning (ML) [12]. As image processing methods advanced, researchers started incorporating deep learning models into them. The modern structures also served several agricultural functions. Drought and consequent food insecurity occurred in parts of the world for reasons that likely included crop diseases. It is estimated that plant diseases cause a yearly average global crop output loss of 16

* Corresponding author: mohdaliff@unikl.edu.my

percent. Furthermore, conventional methods of disease control call for the extensive use of crop protection products that pose risks to both humans and the natural world.

In precision farming, computer vision and deep artificial intelligence have made huge strides forward over the past few years. Applications for precision agriculture help find and sort diseases and pests, and they also teach farmers how to spot illnesses right away [13]. The main idea behind precision agriculture [14] is to find and classify diseases early on. With computer vision, different machine learning and deep learning methods are used to find and sort plant leaves into those that are healthy and those that are sick. The pictures taken of healthy and sick leaves are used to teach the model how to group the leaves. Most vision-based options on the market today need high-resolution images with a clear background. Picture of leaves were taken with HD camera from drone and computer vision methods in this project. To find out what was needed, the dataset was tested using different object recognition and classification methods. The pre-processed dataset worked well with CNN classifier, but Alexnet, a deep learning method, did better for classification.

2 Related works

There are many diseases that can affect bananas, such as banana Sigatoka and banana speckle. Mycosphaerellafijiensis is a fungus that is responsible for black Sigatoka [15]. Tiny chlorotic patches are the first sign, followed by brown streaks that border the leaf veins. Spots on leaves are caused by fungi. The patches, which are first a lighter brown, eventually become larger and black. If the plant isn't treated for these diseases, it will die. However, if they are caught in time, they can be dealt with, and the plant salvaged. Patel et al. (2021) note that a method to automatically identify and recognize banana diseases is crucial considering the global shortage of resources and abilities in banana pathology [16]. Bananas of different varieties may be rendered unusable if their vasculature is severely damaged by environmental stresses (such as soil type, temperature, crop intensification, drainage, and so on).

A serious disease that reduces banana production is fusarium wilt. A fungus in the soil seems like the most likely culprit. Panama disease, or Fusarium wilt, goes by a few other names.

In their recent article, Miguel Dita et al. (2018) summarizes what is currently known about banana Fusarium wilt and provide explanations for the disease's impact on plant health, soil composition, and microbiota [15]. Intensity is finally explored together with routines, their effects on health, and their causes. It is also possible for this disease to be transmitted through contact with soil or water.

Caused by ascomycete fungi, Black Sigatoka is most likely due to Mycosphaerellafijiensis. It's also known as a black leaf streak. The plant's tender young leaves reveal the first signs of a problem. The following describes the symptoms and transmission of black Sigatoka disease and was proposed by Bhamare Sandip P et al. (2013). Small spindle-shaped spots, with a grey spot in the middle and a yellow halo spot running parallel to the veins, will appear on the leaves. Fruits with a severe illness turn pink, and their sizes and flesh quality suffer as a result [17]. The disease can be carried on the wind, in the rain, in the water, or on the old, rotting leaves and plants.

The symptoms of Bunchy Top disease include leaf atrophy, dark green vein lines, and phloem tissue damage. A plant infected in this way will not bear fruit, or if it does, the yield will be low, and the fruit will be distorted or deformed. This illness causes severe stunting, and the top of the pseudostem bunching remains static rather than expanding. While the chlorate margins at the leaves' tips are a distinguishing feature, the overall form and texture of the leaves are stiff and upright, making them smaller and thinner than the typical leaves of plants.

Banana leaf infections, sometimes known as Moko Disease, were the subject of a proposed study by Mondal, B., et al., in 2012. According to the author, infected plants' leaves don't turn yellow but instead take on a pale yellowish hue; they also develop more slowly than healthy plants and may experience leaf withering [18]. The plants will begin to droop due to the discoloration. The plant's vascular system turns a dark brown colour when it is severed. The transmission of the bacteria happens through the afflicted plant material and soil.

These days' farmers face a wide range of challenges. Climate change, soil health, weed and insect proliferation, increasing population, increased urbanization, and decreasing environmental conditions are all problems that affect the entire planet. Drones are commonly utilized in fields in industrialized nations to aid farmers and further the practice of "Precision Agriculture" [14]. In the coming years, drones will also become increasingly commonplace on both large and small farms in developing countries. Modern farmers currently employ UAVs and other high-tech equipment for crop monitoring and forecasting. Information on crop yields, livestock well-being, soil quality, fertilizer assessments, weather patterns, and precipitation totals are just some of the data that may be collected by drones. While drones have many applications—from photography and agriculture to security and warfare—flying and navigation are their primary strengths. Drones can be sent into flight thanks to their power source, which can be a battery or fuel. To maximize performance and minimize weight, drone frames are typically made from composite materials. The controller is used to launch, navigate, and land the drone from a safe distance.

Multiple machine learning methods were analysed by Vipinadas et al., and a four-step plan was developed as a result. Banana leaves were photographed in Step 1 using a standard digital camera. Preprocessing comes next and entails activities like scaling and morphing. Using the Adaptive Contrast Map system, an RGB (Red, Green, Blue) image of YCbCr (Luminance, Chrominance) colour information is transformed into a grayscale image, and then into a binary image, for use in the segmentation process. The next step is an adsorption procedure, during which the leaf's colour, texture, and shape are removed. Then follows the most essential phase: classification, which is done out using an SVM classifier as a detector. Finally, the classifier's performance in determining if a leaf was infected is evaluated [19].

Using an image processing technology, Tigadi et al. (2016) introduced a computer method for automatic plant identification of various and, eventually, proportional infestation. Photos can be made more impactful by employing image enhancing methods. In addition, the proposed study employs Convolutional Neural Networks to identify banana plant diseases. Database development, image enhancement, high-order feature extraction, and optical character recognition are only few of the steps in the proposed method. Finally, an artificial neural network (ANN) technology was utilized to construct a system for information extraction of pictures and identifying illnesses [20].

Amara et al. [2017] offer an automated, machine-learning-based strategy for categorizing banana-leaf illnesses. The LeNet framework should be utilized as a convolutional neural network to recognize picture huge datasets in this scenario. The preliminary results suggest that the proposed method works even in difficult settings including low illumination, a complicated backdrop, and varying resolution, scale, pose, and orientation of real-world pictures. This demonstrates that with relatively little computational effort, the proposed method can significantly aid in the precise diagnosis of leaf diseases. The promising results of the model will lead to its continued usage in the study of banana and plant diseases [10].

The tall banana plant presents a significant diagnostic difficulty for agriculturalists. The banana leaf and fruit have been seriously impacted by a disease. Considering this, Kumar et al. (2018) present a strategy for early disease diagnosis employing image processing with ANN. Images are gathered, then pre-processed, patterns are identified, attributes are extracted and recognized, and diseases are classified. Experimental simulations in MATLAB were used to achieve results on these photos [21].

An analysis of the available literature has been performed to identify banana leaf diseases. Machine learning classifiers perform the analysis and classification of the data in an automated and effective manner. It is possible to diagnose diseases with the help of algorithms like KNN classifiers, SVM classifiers, ANFIS classifiers, and ANN classifiers. Accuracy of 89.1% and 90.9%, respectively, was achieved by implementing SVM and KNN classifiers for identifying plant diseases such as Black Sigatoka and cordana leaf spot by Akshaya Aruraj et al., (2019). Robert Singh. A. (2020) applied KNN classifiers to the problem of diagnosing plant diseases. The study includes diseases including Bunchy top, BBS, and BBW with an accuracy of 98%.

Banana leaf disease can be detected in its early stages with the use of a machine learning classifier developed by Amara et al. (2017). The two most prevalent banana diseases, Sigatoka and speckle, are the topic of this research. The illness classification method DCNN used by Selvaraj et al. (2019) has a high accuracy of 70% to 99% and a high-performance efficiency. Based on the research, it is strongly formulated that the proposed work will be built on the DCNN classifiers. DCNNs provide a superior performance efficiency than other classifiers. Furthermore, a real-time dataset detailing all banana leaf illnesses would be used in the proposed effort [22]. The fact that IR 4.0 technology has been utilized extensively in various domains to achieve superior outcomes compared to more traditional approaches is demonstrated by the inclusion of relevant projects [23-26].

3 Proposed method

Using convolutional neural network (CNN) machine learning methods and GoogleNet, the suggested method develops six disease models capable of distinguishing between black Sigatoka, yellow Sigatoka, banana stem weevil, banana aphid, bacterial soft rot, and Panama on banana leaves.

6700 data-enhanced photos of banana leaves were employed in this study's dataset. Banana plantations across Malaysia were surveyed, and infected and healthy leaves were photographed with simple cameras and DJI Tello drone camera for a unified data set. Different diseased leaf regions may be seen in the various image resolutions. Variation in plant size is also present. There is visual evidence of the climatic shift as well. Images of 200 healthy leaves, 250 with leaf spot disease, and 200 with sigatoka were gathered from farms in Johor and Selangor. The sizes of the pictures varied. The dataset was constructed from a variety of sources, including both collected photographs and public datasets obtained from places like GitHub and Flickr. The public datasets used included 45 photographs of healthy leaves, 200 images of leaves with the Leafspot disease, and 320 images of the Sigatoka disease. Leaves affected with these diseases frequently reveal noticeable markings or sores on it. There is usually a distinctive outward sign that can be used to identify an illness. Each disease's early, middle, and late stages are represented in the database as well. Leaf samples are analysed in a lab or professionals visually assess plants to identify and classify diseases in the collection. The quality of the dataset and the accuracy of its labelling determine the performance of the models.

The photos included in the collection all use the RGB colour mode. Each picture has had its data enhanced by procedures like flipping, rotating, zooming, and cutting. These methods of enhancing data are useful for preventing model overfitting. Deep learning algorithms outperform machine learning algorithms [15], albeit suffering from the same overfitting problem. For CNN classification, the images are shrunk to 150x150 pixels, whereas those used to train on the Alexnet [16] dataset are expanded to 250x250. By adjusting the size of the dataset, we can speed up the training of the algorithms. Then, for enhanced performance, the bicubic non-adaptive interpolation algorithm was performed to each image [17]. Before being divided into black Sigatoka, yellow Sigatoka, banana stem weevil, banana aphid, bacterial soft rot, and Panama categories, the pictures dataset was mixed up.

MATLAB is a software package that facilitates computational mathematics, programming, and data visualization. It provides an interactive setting with hundreds of in-built elements for technical computing, graphics, and animations. A popular acronym for "Matrix Laboratory," MATLAB stands for "Matrix Laboratory. MATLAB was first developed to implement a simple technique for matrix software. As a result, it can be combined with many approaches to programming, such as functional, Object-Oriented, and Visual. Since "matrix" is part of the name, it should come as no surprise that MATLAB does calculations using mathematical matrices and arrays. All MATLAB data types, including integers, characters, and strings, store information in an array.

MATLAB includes its own tools that streamline common tasks. Applications can be written in this high-level language, and numerical calculations can be performed. In addition, it provides a lively atmosphere for iteratively exploring, designing, and solving problems. For solving ordinary differential equations, as well as for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration, it provides a comprehensive set of mathematical procedures. It has built-in visuals for showing data and capabilities for creating custom plots. The MATLAB programming interface provides tools for enhancing performance and maintaining maintainable programs. There are tools available for making custom GUIs for software.

Aerial photography may be enjoyed conveniently with the Tello App's extra flight modes, real-time image sharing interface, camera, and videorecording features. Drone parameters, software updates, and calibration may all be managed through the Tello app. Attitude mode allows for quick adjustments to be made while the drone is in flight. The drone will automatically activate if its visual positioning system fails, and it loses its ability to determine its position in the sky. Because it is so much more susceptible to the impacts of flight conditions like weather, pilots should land it as soon as possible in a safe spot. There are three primary flight modes available to pilots: manual, attitude, and intelligent. When the Tello EDU is flown manually, the pilots can adjust the drone's heading, speed, altitude, and side-to-side movements with nothing more than the app's digital joysticks. Also, operators have control over the drone's speed, which can be set between 8.9 mph and 17.8 mph. Bounce mode, 8-dimensional flips, and Throw & Go are just a few of the clever flying modes available in the Tello App for the Tello EDU.

The primary topic of this research is a comparison of different methods for classifying banana leaves as either healthy or diseased. Black Sigatoka, yellow Sigatoka, the banana stem weevil, the banana aphid, the bacterial soft rot, and Panama are the six categories into which the dataset was sorted. Diseases may appear identical early in the infection process; thus, experts have developed a system for distinguishing between them. Different permutations of the enhanced dataset that has been separated into a training set and a testing set are also examined. The suggested method can determine if a disease is present in the leaf, extract relevant features from the photos, and minimize the overfitting problem.

4 Results and discussion

To accommodate the additional layers and the new function to diagnose the disease, the Convolutional Neural Network designed for this project relies heavily on the pre-trained neural network. This unique Convolutional Neural Network is trained for the diagnosis of diseases in banana plants, using a total of 6700 data collected to train each disease. Table 1 shows the CNN training parameters for this project. The 6700 databases are trained using the Googlenet network, hence 144 values are present in the net layer. Validation can occur as often as every 665 iterations. The rate of learning for this image processing method is 0.0003. The processing power of the laptop limits the duration of the program's execution to no more than 10 epochs.

Table 1. CNN training parameters.

CNN Evaluation	Values
Net Layer	144
Maximum Iteration	665
Validation Frequency	665
Learning Rate	0.0003
Type of Net	GoogleNet
Epochs	10

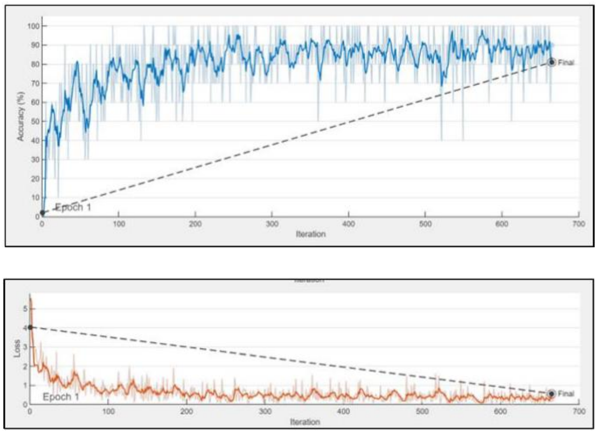

Fig. 1. Accuracy and loss graph of CNN training.

The choice of a neural network architecture for identifying banana plant diseases depends on various factors, including the characteristics of the dataset, the nature of the task, and the computational resources available. Using object identification methods such as R-CNN or Faster R-CNN might be excessive because the main objective of this research is to classify plant photos into several disease groups, and the exact placement of individual lesions is not necessary. When precise object localization within photos is crucial, these models are created for the job. In addition, since the main goal is classification and the dataset mostly includes pictures of well characterized diseases, simpler architectures such as AlexNet or other picture classification models might work better. Both R-CNN and Faster R-CNN necessitate more detailed annotations for object bounding boxes, which increases their computational expense.

Accuracy and loss on the trained data are shown in Figure 1. The reliability of the system demonstrates its shrewdness and viability for use in real-world testing. The precision of the result our system receives is mostly dependent on the correctness of any neural network model. To determine the loss, we compare the network's predicted output with the observed output. When the training loss is small, a network can acquire knowledge from the dataset, but when it is large, it is unable to do so. Loss function training is essential for neural networks. It can be used to direct the optimization process by gauging the model's comprehension of the training data and the efficacy of its fine-tuning. Training a neural network yields a model with predictions that are consistent with the goal. The gap between the actual and target outputs must be narrowed. Training loss, as contrast to validation loss, evaluates how well a model fits the training data. By extending the system's epochs, we can reduce the loss of training data and validation loss and increase the confidence that the model will produce the desired output in the future.

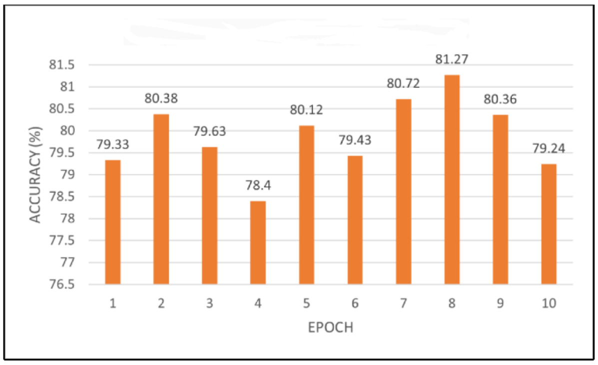

Fig. 2. Average CNN training accuracy for each epoch.

Figure 2 shows average CNN training accuracy for each epoch after being run several times. According to the outcome, epoch 8 has the highest accuracy value at 81.27%. Epoch 4 has the lowest accuracy value, which is 78.40%. In this investigation of the accuracy of trained data, there is a little overfitting at 9 and 10. The study can be stopped at the 8th epoch to get a high percentage of accuracy. In the future, some parameters need to be reviewed so that overfitting in epoch 9 and 10 can be avoided. However, in the current situation the accuracy percentage is at 80.36% and 79.24% is still at a good level and the proposed CNN algorithm can distinguish 6 banana tree diseases well.

5 Conclusion

In conclusion, this study underscores the efficacy of image processing techniques, particularly the application of Convolutional Neural Networks (CNNs), in the realm of plant disease identification. The suggested method develops six disease models capable of distinguishing between black Sigatoka, yellow Sigatoka, banana stem weevil, banana aphid, bacterial soft rot, and Panama on banana leaves. The comprehensive process involving image capture, pre-processing, segmentation, feature extraction, and classification has been elucidated, emphasizing their collective importance in achieving accurate and reliable disease detection. The significance of early disease detection in agriculture cannot be overstated, allowing for timely intervention and mitigation of potential damage. The results of this investigation, with epoch 8 yielding the highest accuracy at 81.27% and epoch 4 exhibiting the lowest accuracy at 78.40%, highlight the robustness of the proposed CNN algorithm in effectively distinguishing among six banana tree diseases.

While acknowledging the marginal overfitting observed in epochs 9 and 10, the study emphasizes that terminating the training at epoch 8 yields a commendable accuracy level of 80.36%. Although further parameter adjustments may be explored to mitigate overfitting in subsequent epochs, the current accuracy percentages of 80.36% and 79.24% still validate the efficacy of the CNN algorithm.

Future research should focus on refining parameters to address overfitting concerns and enhancing the algorithm's predictive capabilities. Overall, this study contributes valuable insights to the field of plant disease identification, offering a promising approach for proactive disease management in agriculture.

Acknowledgment

The authors gratefully acknowledge to the Majlis Amanah Rakyat (MARA) for financial supports given under the Dana Penyelidikan Dan Inovasi Mara (DPIM) 2023 (MARA.600 – 6/4/3 Jilid 2 (75)).

References

1. M. Aliff, N. F. Hanisah, M. S. Ashroff, S. Hassan, S. F. Nurr, N. S. Sani, Development of Underwater Pipe Crack Detection System for Low-Cost Underwater Vehicle using Raspberry Pi and Canny Edge Detection Method, International Journal of Advanced Computer Science and Applications, 13, 11 (2022)
2. A. Syamim, M. Aliff, M. Ismail, S. Izwan, N. Samsiah, M. U. Syafiq, Application of Fuzzy Logic in Mobile Robots With Arduino and IoT, 7th International Conference on Automation, Control and Robotics Engineering (2022)
3. M. A. A. Sani, M. A. Rozidi, M.U.S. Sama'in, N.S. Sani, Development of a Speed Control System Using Face Recognition. In: Ismail, A., Mohd Daril, M.A., Öchsner, A. (eds) Advanced Transdisciplinary Engineering and Technology. Advanced Structured Materials, 174 (2022)

4. M. Aliff, N. A. Kadir, M. I. Yusof, S. Hassan, N. S. Sani, H. Mahmud, Implementation of a Smart Shaded Plant House with Arduino Microcontroller and IoT for Optimal Plant Growth using Fuzzy Logic Control, In Proceedings of the 2023 International Conference on Robotics, Control and Vision Engineering (2023)
5. N. S. Sani, A. H. A. Rahman, A. Adam, I. Shlash, M. Aliff, Ensemble Learning for Rainfall Prediction, International Journal of Advanced Computer Science and Applications, 11, 11 (2020)
6. N. S. Sani, I. Shlash, M. Hassan, A. Hadi, M. Aliff, Enhancing Malaysia Rainfall Prediction Using Classification Techniques, Journal of Applied Environmental and Biological Sciences, 7 2s (2017)
7. A. Aruraj, A. Alex, M. S. P. Subathra, N. J. Sairamya, S. T. George, S. E. V. Ewards, Detection and Classification of Diseases of Banana Plant Using Local Binary Pattern and Support Vector Machine. 2nd International Conference on Signal Processing and Communication (ICSPC), Coimbatore, India (2019)
8. A. Fuentes, S. Yoon, S. C. Kim, D. S. Park, A robust deep-learning-based detector for real-time tomato plant diseases and pests' recognition, Sensors, Switzerland (2017)
9. N. A. B. Mary, A. R. Singh, S. Athisayamani, Banana leaf diseased image classification using novel HEAP auto encoder (HAE) deep learning, Multimed. Tools Appl., 79 (2020)
10. J. Amara, B. Bouaziz, A. Algergawy, A deep learning-based approach for banana leaf diseases classification, Lecture Notes in Informatics (LNI), Gesellschaft für Informatik (2017)
11. J. G. A. Barbedo, Plant disease identification from individual lesions and spots using deep learning, Biosystems Engineering, 180, Elsevier (2019)
12. D. Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat, N. Batra, PlantDoc: A Dataset for Visual Plant Disease Detection, CoDS COMAD (2020)
13. M. Turkoglu, B. Yanikoglu, D. Hanbay, PlantDiseaseNet: convolutional neural network ensemble for plant disease and pest detection, Signal, Image and Video Processing (2021)
14. M. Arsenovic, M. Karanovic, S. Sladojevic, A. Anderla, D. Stefanovic, Solving current limitations of deep learning-based approaches for plant disease detection, Symmetry 11, 939 (2019)
15. Dita, Miguel, et al., Fusarium wilt of banana: current knowledge on epidemiology and research needs toward sustainable disease management, Frontiers in plant science 9, 1468 (2018)
16. Patel, Ankita, Agravat, Shardul, Banana Leaves Diseases and Techniques: A Survey (2021)
17. Bhamare, Sandip P., and Samadhan C. Kulkarni. "Detect ion of black Sigatoka on a banana tree using image processing techniques." IOSR Journal of Elect ronics and Communication Engineering (2013): 60-65.
18. Mondal, B., et al. "Bacterial wilt of banana in West Bengal, India." International Journal of Plant Protection 5.2 (2012): 227-231.
19. M. J. Vipinadas, Thamizharasi, Banana Leaf Disease Identification Technique, International Journal of Advanced Engineering Research and Science, 3, 6 (2016)
20. B. Tigadi, B. Sharma, Banana Plant Disease Detect ion and Grading Using Image Processing, (2016)
21. V. Kumar, Gokulpriya, Banana tall plant disease detect ion and classification using image processing and artificial neural network, International Journal of Advanced Science and Engineering Research, 3, 1 (2018)
22. M. G. Selvaraj, A. Vergara, H. Ruiz, et al., AI-powered banana diseases and pest detection. Plant Methods, 15, 92 (2019) https://doi.org/10.1186/s13007-019-0475-z
23. S. Shimooka, K. Katayama, T. Akagi, S. Dohta, T. Shinohara, T. Kobayashi, M. Aliff, Development of Automatic Ladder Climbing Inspection Robot Using Extension Type Flexible Pneumatic Actuators, International Journal of Automotive and Mechanical Engineering, 19, 1 (2022)
24. M. Aliff, M. Imran, S. Izwan, M. Ismail, N. Samsiah, T. Akagi, S. Dohta, W. Tian, S. Shimooka, A. Athif, Development of Pipe Inspection Robot using Soft Actuators, Microcontroller and LabVIEW, International Journal of Advanced Computer Science and Applications, 13, 3 (2022)
25. M. A. A. Sani, M. D. A. Azharshah, M. I. Yusof, M. U. S. Sama'in, N. S. Sani, Development of a Low-Cost Hydroelectric Generation System for Application on Water Pipelines, Advanced Transdisciplinary Engineering and Technology, Advanced Structured Materials, 174 (2022)
26. W. Tian, Y. Suzuki, T. Akagi, S. Dohta, W. Kobayashi, T. Shinohara, S. Shimooka, M. Aliff, Development of Wrist Rehabilitation Device Using Extension Type Flexible Pneumatic Actuators with Simple 3D Coordinate Measuring System, International Journal of Automotive and Mechanical Engineering, 18, 4 (2021)