Deep Learning approaches for the detection, classification, and analysis of sugarcane leaf disease

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Article Info

Article History

Keywords
Machine Learning, Disease Prediction, Deep Neural Networks, Risk Analysis

Abstract

Sugarcane infections are a major threat to the sugarcane sector because they lead to widespread destruction of diseased crops, a decline in farming, and significant financial losses for small-scale farmers. Should early sickness detection and modern technology such as machine learning proves to be practical, the harm inflicted by this farming catastrophe could potentially be avoided. Consequently, deep learning—a relatively recent advancement in machine learning—offers a solution to this issue. This study suggests multiple deep learning models using 20,000 shots of sugarcane—both healthy and sick or diseased—from a collection of sugarcane photos. Deep learning models are the trained models that were employed in the investigation. Out of all the trained models, the one that has received the most training will have the highest accuracy. The trained models accomplish this work by identifying and categorizing photos of healthy and diseased sugarcane leaves according to a pattern of defects and healthy leaves. Farmers may be able to maintain their crops and sources of income if deep learning algorithms are used to identify sugarcane diseases early on.

Introduction

Deep learning models are the trained models that were employed in the investigation. Out of all the trained models, the one that has received the most training will have the highest accuracy. The trained models accomplish this work by identifying and categorizing photos of healthy and diseased sugarcane leaves according to a pattern of defects and healthy leaves. Farmers may be able to maintain their crops and sources of income if deep learning algorithms are used to identify sugarcane diseases early on.

One of the most important aspects of managing crop diseases is preventing larger losses, which can be achieved by early crop disease identification and preventative actions. The conventional approach to identifying and diagnosing illnesses of sugarcane is usually done by hand. Recently, an automated technique for handling these tasks was created to minimize disruptions and reduce the time required to complete them manually or conventionally.

One popular method that has been used to address these problems with plant disease detection and identification is convolutional neural networks. Deep artificial neural network topologies that are employed in the learning process are incorporated into the Convolutional Neural Networks (CNN) technique. Only recently, and to a limited extent, have deep learning techniques been used in agriculture [2], especially in the area of plant disease identification. Convolutional neural networks were the main deep learning technique used in this study (CNN). One of the best ways to model complex processes and perform pattern recognition in large-scale data applications.

A great deal of scientific research has been done on the biological elements of plant diseases that affect sugarcane. Plant disease detection and diagnosis has proven to be an interesting field that needs careful consideration. Food safety is impacted by plant diseases, which are especially harmful to small-scale farmers whose livelihoods depend on a healthy crop output. Farmers and consumers will benefit from higher-quality sugarcane production brought about by early diagnosis of these ailments. To stop additional damage, prophylactic actions are implemented through early detection of sugarcane diseases. In sugarcane, the majority of disease identification, diagnosis, and treatment are often performed by hand.

CNNs are a particular kind of neural network that rely on Artificial Neural Networks (ANN) for Deep Learning techniques. Because of its effectiveness and precision, particularly in the identification of plant diseases, DL has become more and more popular in the agricultural industry. CNNs are excellent at managing intricate procedures and seeing patterns in images. The primary objective of this work is to train the database with a neural network by producing a labeled dataset. The trained neural network is tested and its correctness is ascertained. The next step is to create a Graphical User Interface (GUI) that makes sugarcane disease detection easy to use. Plant diseases frequently affect sugarcane plants that are in growth, which has a detrimental effect on the quality and production of the crop and costs the agriculture sector money. Disease control is a challenging task. The plant's leaves develop color spots or streaks, which are signs of a disease. Fungi, bacteria, and viruses are the culprits behind leaf diseases. Hands and the unaided eye are typically used to identify these conditions. Many diseases can be automatically detected by image processing. Because image processing minimizes human labor while producing optimal results, it is essential for the diagnosis of plant diseases.

Literature Review

Sugarcane is the main crop utilized worldwide to manufacture ethanol and sugar. The disease causes growing crops to be eradicated, which results in financial loss. If these illnesses are not treated, small-scale farmers may suffer early discovery of the illness, which is a problem for the sugar industry. Using an image collection of 13,842 sugarcanes with sick leaves, this study evaluated and trained a deep learning model. Accuracy of 95% was attained by healthy leaves. The trained model correctly identified and classified sugarcane pictures into classes that represented healthy, ill, and sick sugarcane leaves. As a result, this work proposes the use of deep learning algorithms to help farmers identify and categorize sugarcane diseases. [1]

One of the numerous difficulties that the farming business looks at is the detection of harvest infections. Automated disease recognition is now possible, nevertheless, thanks to advancements in optical registration and improved computing hardware. Its utility has been shown by results utilizing convolutional neural networks (CNNs) with datasets that are available to the public. The author employed the YOLO and Faster-RCNN item detection algorithms. Our dataset was used to analyze the two companies, and they obtained the highest Mean Average Precision score of 58.13% on the test set. All things considered, the strategy of applying CNNs to a remarkably diverse dataset would get ready for frameworks for automatic infection recognition. [2]

It is now difficult for farmers to monitor every plant in the growing zone and detect any signs of illness. Algorithms for image processing have been created to act as watchdogs by recognizing the disease and its manifestation in the leaf. A combination of several feature extractions Gray Level Co-occurrence Matrix (GLCM) and Principal Component Analysis (PCA) with an SVM classifier has been tried for six significant illnesses that significantly affect sugarcane yield. The accuracy value of the suggested system was 95%. A detailed examination of the causes and symptoms of every disease Sugarcane illnesses are highlighted in this article. A website application designed for our system is meant to be utilized by Farmers. It will benefit them. [3]

According to the author A Narmilan and colleagues, sugarcane white leaf phytoplasma, or white leaf disease, is caused by A phytoplasma that is transferred by leafhopper vectors. The world's sugarcane industries are seriously threatened by white leaf disease (WLD), which mostly affects a few Asian countries, especially Sri Lanka. Hence, a workable and effective technique for accurately monitoring WLD infection is necessary, especially during the first pre-visual phase. This work presents the first technique for sugarcane WLD early detection using high-resolution multispectral sensors mounted on small unmanned aerial vehicles (UAVs) and supervised machine learning classifiers.[4]

Research by S. V. Militante and B. D. Gerardo et al. [5] indicates that outbreaks of plant diseases can pose a serious threat to the safety of our food supply. A tragedy like this one might have been avoided with ML-based early illness detection. DL is a relatively new machine learning technique that is now widely used for applications that need object recognition. The results of the studies suggest that a CNN with a more intricate architecture is more capable of completing this task. Using a subset of the Plant Village dataset, specifically the tomato dataset, they investigate several deep CNNs, including VGGNet, AlexNet, and GoogleNet, as well as a simple two-layer CNN as a baseline for tomato plant disease recognition tasks.

Manavalanet al.'s investigation [6] indicates that the disease poses a problem to the sugarcane industry since it destroys afflicted crops, limits cultivation, and incurs financial losses for farmers. ML technology can help to avert such losses by detecting diseases early. As a result, DL offers a fascinating method for using machine learning to solve this problem. They classified and identified sugarcane diseases using three different DL models. The LeNet, StridedNet, and VGGNet models are compared in the research architecture. It also determines which model is best for classifying and diagnosing diseases related to sugarcane. Of the three models, StridedNet had the lowest accuracy rate in identifying illnesses related to sugarcane, while VGGNet has the highest.

The dataset used by the author is based on images gathered from various farms using various pieces of technology. The classifier gets so strong that it produces accurate results in daylight. Images are obtained straight from farms using various cameras; thus the developed algorithm is made to be able to classify diseases with good accuracy regardless of the orientation, field of view, image resolution, or angle of the photographs. [7]

In this paper, a novel method for simultaneously performing the segmentation of individual leaf examples and the identification of infected regions is presented. It utilizes a deep learning architecture. End-to-end training is made possible by the use of a multi-task loss function in conjunction with a unified feature map. Using this paradigm on a field maize dataset affected by Northern Leaf Blight (NLB) disease was the task of this study. When compared to manually annotated ground truth data, the experiment's results showed a notable correlation of 73% in illness severity while maintaining a real-time efficiency of 5 frames per second. [8].

Although only one side of the leaf was utilized for classification, foliar plant diseases have been identified by artificial intelligence. Phytopathology states that a number of diseases show similar symptoms on the upper leaf surface but different symptoms on the lower surface. Accuracy in diagnosing plant diseases can be improved by considering the symptoms on both leaf surfaces. Examining the resulting snapshot is crucial in determining whether the leaf is visible in this condition from its top or bottom side. The research, which made use of botany literature, found that color functions as a helpful classification feature by making the side facing the sun greener and the side facing the shadow darker. [9]

According to the author, choosing a classification method might be challenging because the input data can have a variable impact on the quality of the results. K-Nearest Neighbor Classifier (KNN), Probabilistic Neural Network (PNN), Genetic Algorithm, Support Vector Machine (SVM) and Principal Component Analysis, Artificial Neural Network (ANN), and Fuzzy Logic are a few instances of several classification algorithms. [10]

One crop that is high in sucrose, a kind of sugar, is sugarcane. It can be used to make jaggery, white sugar, and a number of by-products, including as molasses and bagasse. Sugarcane is used to create 75% of the sugar produced globally. India is the world's second-largest producer and user of sugar. Additionally, India is the second-largest nation in the world in terms of its agricultural industry. [11].

Sugarcane juice, with its natural alkalinity, also guards against breast and prostate cancer. It is also beneficial for maintaining normal blood pressure levels and the healthy operation of the kidneys and liver. However, disease epidemics affecting the sugarcane plant have destroyed crops [12].

Infected sugarcane significantly reduces crop productivity. Monitoring health and disease is crucial for efficient agricultural production. Image processing and deep learning (DL) are used to diagnose a sick stem, leaf, color fruit, diseased size, shape, and area of leaves, etc. [13].

The suggested method demonstrated how altering CNN parameters based on the image and areas that need to be identified could improve the performance of Faster R-CNN architecture. For pertinent factors, the suggested strategy produced better results than the contemporary techniques outlined in earlier research. Therefore, it is anticipated that the method will shorten the time required to diagnose sugar beet leaf spot disease in large production areas, as well as shorten the time required to determine the illness's severity and course due to human error. [14].

The illness's severity is the only information the author provides; crop loss due to disease can range from 10% to 50% [15]. Plant cytochrome oxidase (cox) LAMP primers, which amplify a housekeeping gene in plants, were used as controls. With the use of a commercially available master mix and a real-time fluorometer, LAMP tests enabled the quick detection of the Sugarcane white leaf (SCWL) phytoplasma at 63 °C in just 30 minutes. The study's conclusions indicated potential use for the assay by contrasting the labor-and cross-contamination-intensive conventional methods for SCWL detection in the field with the LAMP-based test using 16SrXI SCWL primers [16].Through training, advances in computer vision could expand and improve plant protection precision, enabling precision farming. [17].

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As controls, plant cytochrome oxidase (cox) LAMP primers were utilized, which amplified a housekeeping gene in plants. The SCWL phytoplasma was quickly detected at 63 °C in just 30 minutes using LAMP tests and a commercially available master mix and real-time fluorometer. By comparing the labor-and cross-contamination-intensive traditional methods for SCWL detection in the field with the LAMP-based test utilizing 16SrXI SCWL primers, the study's conclusions suggested a potential application for the assay [18]. accuracy farming could be supported by the expansion and enhancement of plant protection accuracy made possible by computer vision training advancements. [19].

Image processing was first used in many research to identify and categorize sugarcane diseases. The characteristic was obtained and the infection status was determined using an image processing technique. By analyzing the color and pattern of the illness, it can identify the affected areas and classify the disease's severity [20]. Form features in photos of ill leaves processed directly with an image processing technique. Alternatively, diseases can be classified using the offered machine learning (ML) methodologies of support vector machines (SVM) and K-means clustering. Similarly, the DL techniques for the illness classification employed artificial neural networks (ANN) and convolutional neural networks (CNN). The use of DL methods for plant disease and pest identification has been extensively studied recently [21]. Even after a range of approaches and techniques have been developed, there is still opportunity for improvement [22].

This study offers a system for categorizing and identifying the most prevalent plant diseases that is driven by artificial intelligence (AI). The ill areas are divided by the suggested framework using the E color difference image segmentation. To extract rich, useful feature vectors, color (RGB, HSV) and texture (LBP) histograms are also used. [23] sugarcane leaf, and the outcomes demonstrate that it was successful at the highest accuracy of 95.40%. CNN use the networks LeNet, VGGNet, and StridedNet to locate and classify illnesses. Padilla and associates created a small gadget that uses SVM to identify yellow sugarcane leaves with spot disease. [24]

Plant disease identification using pattern analysis raises production issues that lower agricultural yield. By increasing accuracy, speeding up scientific and innovative transitions, and automating the selection of illness spot traits, deep learning offers solutions. Finding diseases early on is crucial to cutting losses. Viral diagnosis on smartphones has become simpler thanks to the convergence of deep learning-driven advances in computer vision with the growing popularity of smartphones. Applying the CNN algorithm and using photographs as training data is an essential step in this process. The identification and detection of plant diseases is one of the primary variables influencing harvest and deficits in agricultural productivity. Differentiating plants according to traits like spots or color changes may be made easier by looking closely at any obvious anomaly on the plant. Investigation of plant infections is the term for this procedure. Since horticulture depends on plants being healthy, identifying plant diseases is a challenging task that requires a lot of time, energy, and understanding of both plants and the science underlying disease detection. A thorough comprehension of the subject and a significant deal of experience are necessary for accurate identification. [25]

Crop diseases mentioned by Park et al. [26] are the most important factor because they reduce crop productivity by 20-30% when they infect a crop. Agricultural diseases have a significant impact on crop productivity. When the condition is doubtful, farmers have to rely on professional judgment or personal experiences. When a farmer sends a leaf image taken with a smartphone to an analysis engine system, the process for diagnosing and predicting diseases is examined. They developed a system for diagnosing the condition that included two convolutional and three fully connected networks.

When running on a central processing unit (CPU), the model has an accuracy of 89.7%. Plant diseases studied by Dandawate et al. [27] are the most significant factor reducing agricultural output in terms of both quality and quantity. Farmers have a difficult time diagnosing and managing plant diseases. Finally, the testing results show that this system can accurately classify leaves with an average accuracy of 93.79%. Militante et al. [28] studied the trained model that was 96.5% accurate. They identified and detected 32 different plant species and diseases using a CNN. Using the trained model, real-time images were assessed for the identification and detection of plant diseases. Their proposed methodology, which has a 96.5% accuracy rate, can help farmers identify and categorize plant diseases.

Hu et al. [29] analyzed the infections in tea leaves may be reliably and promptly recognized, which will help control and avoid them. According to experimental results, the proposed method has a 92.5% average identification accuracy, which is higher than that of traditional Machine Learning (ML) techniques and traditional DL strategies. The upgraded model has fewer parameters and requires less iteration to achieve convergence than the visual geometry group-16 (VGG16) and AlexNet DL network models. According to the findings of the studies, the recommended model has the advantages of having few parameters, a high degree of identification accuracy, and a fast rate of identification.

Suryawati et al. [30] studied that the outbreaks of plant diseases can pose a serious threat to the safety of our food supply. With ML-based early illness detection, such a tragedy could be avoided. DL, a relatively new ML method, is already widely used for tasks requiring object recognition. According to the findings of the studies, a CNN with a deeper architecture performs this function better. They use a subset of the Plant Village dataset, specifically the tomato dataset, to test several deep CNNs, including VGGNet, AlexNet, GoogleNet, and a simple two-layer CNN as a baseline for tomato plant illness identification tasks.

Militante et al. [31] analyzed that the sugarcane disease is a threat to the sugarcane industry because it destroys infected crops, reduces cultivation, and costs farmers' money. ML technologies can help to prevent such losses by detecting diseases early. As a result, DL is an intriguing approach to using machine learning to solve this problem. To find and classify sugarcane diseases, they used three DL models. The LeNet, StridedNet, and VGGNet models are compared in the study architecture. It also determines which model is best at classifying and figuring out sugarcane diseases. In detecting sugarcane diseases, out of the three models, the VGGNet has the best accuracy rate, while StridedNet has the lowermost.

Huang et al. [32] set out a study to ascertain the accuracy with which the spectro-optical, Photochemical Reflectance Index (PRI) measured the wheat yellow rust Disease Index (DI) and how well it could be used to hyper spectral imaging for disease detection. The growth of wheat plants with varied levels of yellow rust infection was measured five times over the course of two seasons to determine the canopy reflectance spectra and DI. During the second season, the field site was also photographed from the air using hyper spectral imaging. The findings showed that PRI can detect winter wheat yellow rust and can be utilized to develop an image sensor for usage in space or in the air for winter wheat fields.

A new learning paradigm known as Graph Transformer Networks (GTNs), created by Lecun et al. [33], enables the global teaching of multimodal systems while minimizing a performance metric using gradient-based approaches. In order to read a bank cheque, a graph transformer network is also used. By combining CNN character recognizers with international training methods, it offers unparalleled correctness on both commercial and private inspections. The same is used in the commercial world and reads millions of cheques every day.

CNNs have been shown to be capable of replacing manual feature extractors. GTNs have been demonstrated to lessen the requirement for manually created heuristics, labor-intensive labelling, and human parameter regulation for systems that recognize documents.

Hou et al. [34] showed that a virus known as Grapevine Leafroll Disease (GLD) can quickly infect vineyards and reduce grape yield by more than 60% under the right meteorological conditions. To prevent the spread of GLD infection, accurate diagnosis and objective evaluation of GLD distribution are required, especially in the early stages of infection. In order to precisely treat the disease, this study used the Ant Colony Clustering Algorithm (ACCA) to identify GLD spectrum anomalies on four GLD-infected vineyards. GLD was classified into three stages based on the severity of the infection: GLD1, GLD2, and GLD3.

Nagvani et al. [35] exploited ML algorithms can be used to identify diseases because they apply primarily to data and prioritize the results of particular activities. This study compares machine learning classification methods for plant disease detection and presents the processes of a general plant disease detection system. It was found in this study that CNN has a high level of accuracy and can identify more diseases across various crops. This review compares and contrasts five various machine learning classification algorithms for identifying plant diseases. The findings show that a greater percentage of illnesses are successfully detected by the CNN classifier

Related Work

A. Image Dataset Acquisition

A camera is used to manually collect a picture dataset. The names of the many classes of photographs of sugarcane leaves in varying states of health are saved with the photos once they have been improved and segmented. The obtained image dataset contains 13,842 images across multiple classifications. All images are stored in the uncompressed file; PNG or JPG files with an RGB base are accepted.

B. Pre-Processing of Images

Pre-processed images include smaller photos, photos that have been cropped, and better photos. We use scaled, colorful, 96x96 resolution images for additional processing.

C. Feature Extraction

The convolutional layers features are extracted from the scaled pictures. Rectified non-linear activation function (ReLU) is employed after convolution and other types of pooling. Maximum and average pooling reduces the pool's dimensions. Extraction of features [4]. Together, the pooling and convolution layers will function as a filter to produce features.

D. Classification

Convolutional and pooling layers are utilized for feature extraction, and fully linked layers are employed for classification. The sugarcane leaves are arranged in this way based on whether or not they have a disease.

Disease Name	Symptoms	Conditions
Red Rot	Leaf spindles dry out. Stalks become hollow and smeared.	Diseases occurs through air, rain splash and soil
Wilt	leaves turning yellow and drying, canes shrinking or withering	Monsoon and post monsoon periods
Smut	A whip containing black powdered spores and covered in a clear silvery membrane	Hot Dry Weather
Leaf scald disease	Since chloroplasts are not created, the disease is caused by sections of the leaf that turn pale green (chlorotic).	drought, waterlogging, and low temperature
Red striped disease	The lower surface of the leaf has whitish flakes that match the red blemishes on the upper surface.	Moist humid conditions
Mosaic disease	Young leaves pressed up against a light source display chlorotic, and a consistent green area creates a mosaic design.	Spread through diseased seed material and cutting knife
Rust	The earliest noticeable symptoms of typical leaf rust are tiny, long, yellowish dots.	High humidity and warm temperature
Sugarcane yellow leaf disease	yellowing of the leaf midrib's bottom surface.	Dry weather conditions

Table1 Disease and symptoms of sugar cane disease.

Conclusion

In summary, this paper's proposed system has demonstrated the considerable promise of machine learning and deep learning approaches for the early identification and diagnosis of sugarcane illnesses. By using these methods, information from photos of sugarcane leaves may be extracted and utilized to train a model that will identify which leaves are healthy and which are unhealthy. These models have demonstrated extremely high accuracy and have the potential to completely change the way illnesses specific to sugarcane are treated. Nevertheless, before farmers can use these methods extensively, a few issues still need to be resolved. The requirement for big datasets of identified photos is one difficulty. The collection of these databases can be costly and time-consuming. Creating models that are resilient to changes in lighting, weather, and other variables is another difficulty. The potential advantages of applying deep learning and machine learning to the prediction of sugarcane disease outweigh these difficulties. These methods could increase crop yields, decrease crop losses, and result in financial savings for farmers. These methods will probably be utilized more frequently as technology advances in order to raise the yield and general health of sugarcane crops.

References

[1]S. V. Militante, B. D. Gerardo and R. P. Medina, "Sugarcane Disease Recognition using Deep Learning," 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE), Yunlin, Taiwan, 2019, pp. 575-578, doi: 10.1109/ECICE47484.2019.8942690.

[2] Prince Kumar , Mayank Sonker and Vikash, “Research Paper On Sugarcane Diseaese Detection Model” SCSE, Galgotias Article History: Received: 10 November 2020; Revised 12 January 2021 Accepted: 27 January 2021; Published online: 5 April 2021.

[3] K. Thilagavathi, K. Kavitha , R.Dhivya Praba , S.V.Arockia Joseph Arina and R.C.Sahana “Detection of Diseases in Sugarcane Using Image Processing Techniques” Biosc.Biotech.Res.Comm. Special Issue Vol 13 No 11 (2020) Pp-109-115.

[4] A Narmilan, F Gonzalez, ASA Salgadoe, K Powell ” Detection of white leaf disease in sugarcane using machine learning techniques over UAV multispectral images” Drones, 2022 - mdpi.com Drones 2022, 6(9), 230; https://doi.org/10.3390/drones6090230 Received: 21 August 2022 / Accepted: 24 August 2022 / Published: 1 September 2022.

[5] S. V. Militante and B. D. Gerardo, "Detecting sugarcane diseases through adaptive deep learning models of convolutional neural network," 2019 IEEE 6th International Conference on Engineering Technologies and Applied Sciences (ICETAS), Kuala Lumpur, Malaysia, 2019, pp. 1-5, doi: 10.1109/ICETAS48360.2019.9117332.

[6] Manavalan, R. (2021). Efficient Detection of Sugarcane Diseases through Intelligent Approaches: A Review. Asian Journal of Research and Review in Agriculture, 3(1), 174–184. Retrieved from https://globalpresshub.com/index.php/AJRRA/article/view/1237.

[7] Sammed Abhinandan Upadhye , Maneetkumar Rangnath Dhanvijay , Sudhir Madhav Patil , "Sugarcane Disease Detection Using CNN-Deep Learning Method: An Indian Perspective," Universal Journal of Agricultural Research, Vol. 11, No. 1, pp. 80 - 97, 2023. DOI: 10.13189/ujar.2023.110108.

[8] K. Garg, S. Bhugra, and B. Lall, “Automatic quantification of plant disease from field image data using deep learning,” in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 1965–1972, Waikoloa, HI, USA, January 2021.

[9] A. Sagar and D. Jacob, “On using transfer learning for plant disease detection,” BioRxiv, pp. 1–8, 2021.

[10] V. Tiwari, R. C. Joshi, and M. K. Dutta, “Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images,” Ecological Informatics, vol. 63, Article ID 101289, 2021.

[11] S.V. Militante and B.D. Gerardo, “Detecting sugarcane diseases through adaptive deep learning models of

convolutional neural network," in Procee2019 IEEE 6th International Conference on Engineering Technologies and Applied Sciences (ICETAS), pp. 1–5, IEEE, Kuala Lumpur, Malaysia, December 2019.

[12] D.A.G. V. Padilla Magwili, A. L. A. Marohom, and G. Clyde Mozes, "Portable yellow spot disease identifier on sugarcane leaf via image processing using support vector machine," in Procee2019 5th International Conference on Control, Automation and Robotics (ICCAR), pp. 901–905, IEEE, Beijing, China, August 2019.

[13] N. K. Hemalatha, R. N. Brunda, G. S. Prakruthi, B. V. B. Prabhu, A. Shukla, and O. S. J. Narasipura, "Sugarcane leaf disease detection through deep learning," in Deep Learning for Sustainable AgricultureAcademic Press, Cambridge, MA, USA, 2022.

[14] M. M. Ozguven and K. Adem, "Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms," Physica A: Statistical Mechanics and its Applications, vol. 535, Article ID 122537, 2019.

[15] K. ,ilagavathi, K. Kavitha, R.D. Praba, S.A.J. Arina, and R.C. Sahana, "Detection of diseases in sugarcane using image processing techniques," Bioscience Biotechnology Research Communications, vol. 15, no. 10, pp. 2157–2168, 2020.

[16] N.B. Quoc, "Development of loop mediated isothermal amplification assays for the detection of sugarcane white leaf disease," Physiological and Molecular Plant Pathology, vol. 113, Article ID 101595, 2021.

[17] Y. Shendryk, J. Sofonia, R. Garrard, Y. Rist, D. Skocaj, and P. ,orburn, "Fine-scale prediction of biomass and leaf nitrogen content in sugarcane using UAV LiDAR and multispectral imaging," International Journal of Applied Earth Observation and Geoinformation, vol. 92, Article ID 102177, 2020.

[18] K.-l. Wang, Q.-q. Deng, J.-w. Chen, and W.-k. Shen, "Development of a reverse transcription loop-mediated isothermal amplification assay for rapid and visual detection of Sugarcane streak mosaic virus in sugarcane," Crop Protection, vol. 119, pp. 38–45, 2019.

[19] V. S. Dhaka, S. V. Meena, G. Rani et al., "A survey of deep convolutional neural networks applied for prediction of plant leaf diseases," Sensors, vol. 21, no. 14, p. 4749, 2021.

[20] O. O. Abayomi-Alli, R. Damaˇsevicius, S. Misra, and ˇ R. Maskeliunas, "Cassava disease recognition from low- quality images using enhanced data augmentation model and deep learning," Expert Systems, vol. 38, no. 7, 2021.

Sugarcane streak mosaic virus in sugarcane," Crop Protection, vol. 119, pp. 38–45, 2019.

[21] V. S. Dhaka, S. V. Meena, G. Rani et al., "A survey of deep convolutional neural networks applied for prediction of plant leaf diseases," Sensors, vol. 21, no. 14, p. 4749, 2021.

[22] O. O. Abayomi-Alli, R. Damaˇsevicius, S. Misra, and ˇ R. Maskeliunas, "Cassava disease recognition from low- quality images using enhanced data augmentation model and deep learning," Expert Systems, vol. 38, no. 7, 2021.

[23] A. Almadhor, H. T. Rauf, M. I. U. Lali, R. Damaˇseviˇcius, B. Alouffi, and A. Alharbi, "AI-driven framework for recognition of Guava plant diseases through machine learning from DSLR camera sensor based high resolution imagery," Sensors, vol. 21, no. 11, p. 3830, 2021.

[24] Z. u. Rehman, M. A. Khan, F. Ahmed et al., "Recognizing apple leaf diseases using a novel parallel real-time processing framework based on MASK RCNN and transfer learning: an application for smart agriculture," IET Image Processing, 2021

[25] Silpa Chaitanya P, Harshini K, Moni Priyanka K, Pranavika Sri K and Pavani D, "Plant Disease Detection Using CNN", In: Satyasai Jagannath Nanda and Rajendra Prasad Yadav (eds), Data Science and Intelligent Computing Techniques, SCRS, India, 2023, pp. 47-54. https://doi.org/10.56155/978-81-955020-2-8-5

[26] H. Park, J. S. Eun, and S. H. Kim, “Image-based disease diagnosing and predicting of the crops through the deep learning mechanism”, International Conference on Information and Communication Technology Convergence (ICTC), IEEE, 18-20, pp. 129-131, October 2017. https://doi.org/10.1109/ICTC.2017.8190957.

[27] Y. Dandawate, and R. Kokare, “An automated approach for classification of plant diseases towards the development of futuristic decision support system in Indian perspective”, International Conference on Advances in Computing, Communications, and Informatics (ICACCI), IEEE, Kochi, India, pp. 794-799, 10-13 August 2015. https://doi.org/10.1109/ICACCI.2015.7275707.

[28] Sammy V. Militante, Bobby D. Gerardoij, and Nanette V., “Plant Leaf Detection and Disease Recognition using Deep Learning”, Eurasia Conference on IOT, Communication and Engineering (ECICE), Yunlin, Taiwan, pp. 579-582, 03-06 October 2019. https://doi.org/10.1109/ECICE47484. 2019.8942686.

[29] Hu Gensheng, Yang Xiaowei, Zhang Yan, and Wan Mingzhu, “Identification of tea leaf diseases by using an improved deep convolutional neural network”, Sustainable computing: Informatics and System, volume 24, pp. 102-109, December 2019. https://doi.org/10.1016/j.sus com.2019.100353.

[30] E. Suryawati, R. Sustika, R. Yuwana, A. Subekti, and H. Pardede, “Deep Structured Convolutional Neural Network for Tomato Diseases Detection”, International Conference on Advanced Computer Science and Information Systems (ICACSIS), Yogyakarta, Indonesia, 27-28 October 2018. https://doi.org/10.1109/ICACSIS.2018.8618169.

[31] S. Militante, and B. Gerardo, “Detecting Sugarcane Diseases through Adaptive Deep Learning Models of Convolutional Neural Network”, 6th IEEE International Conference on Engineering Technologies and Applied Sciences (ICETAS), Kuala Lumpur, Malaysia, pp. 1-5, 20-21 December, 2019. https://doi.org/10.1109/ICETAS48 360.2019.9117332.

[32] W. Huang, D. W. Lamb, Z. Niu, Y. Zhang, L. Liu, and J. Wang, “Identification of yellow rust in wheat using in-situspectral reflectance measurements and airborne hyper spectral imaging”, Precision Agriculture, Vol. 8, nos. 4/5, pp. 187-197, 2007. https://doi.org/10.1007/s11119-007-90 38-9.

[33] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition”,
Proceedings of the IEEE, vol. 86 (11), pp. 2278–2324, 1998. https://doi.org/10.1109/5.726791.

[34] Jingwei Hou, Longtang Li, and Jie He, “Detection of grapevine leafroll disease based on 11-index imagery and ant colony clustering algorithm”, Precision Agriculture, pp. 1-18, 25 January 2016. https://doi.org/10.1007/s1119-016- 9432-2.

[35] U, Shruti, V. Nagaveni, and B.K. Raghvendra, “A Review on Machine Learning Classification Techniques for Plant Disease Detection”, 5th International Conference on Advanced Computing & Communication Systems (ICACCS), Coimbatore India, pp. 281-284, 15-16 March 2019. https://doi.org/10.1109/ICACCS.2019.8728415.