International Journal of Electronics and Communication Engineering and Technology (IJECET)
Volume 13, Issue 1, January-April 2022, pp. 39-48. Article ID: IJECET_13_01_006
Available online at https://iaeme.com/Home/issue/IJECET?Volume=13&Issue=1
ISSN Print: 0976-6464 and ISSN Online: 0976-6472
DOI: https://doi.org/10.34218/IJECET_13_01_006

Paper Type: Conference paper
Presentation: Oral Presentation

APPLICATIONS OF MACHINE LEARNING AND DEEP LEARNING IN FARMING: A REVIEW

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ABSTRACT

India is largely an agriculture product producing country. Agriculture in India is facing many challenges like drought, flood, disease, pricing, yield and etc. Precision agriculture is one of the rapidly developing fields. To address current challenges in agriculture, Deep learning stands as a promising technology in precision farming, facilitating the advancement of sophisticated disease detection and categorization methods Plant disease recognition by deep learning, eliminates the need for manual identification of disease features, rendering feature abstraction more objective and enhancing technological efficiency. This paper provides a comprehensive review of machine learning and deep learning techniques applied to detect and classify plant diseases. The paper discusses available datasets for crop and plant disease detection and abstraction followed by a comparative investigation of various algorithms utilized in leaf disease detection.

Key words: Agriculture, Deep Learning, Disease detection

Cite this Article: Halaswamy B. M, Mamatha M. M. Applications of Machine Learning and Deep Learning in Farming: A Review. *International Journal of Electronics and Communication Engineering and Technology*, 13(1), 2022, pp. 39-48.
https://iaeme.com/Home/issue/IJECET?Volume=13&Issue=1

I. Introduction

Indian economic development relies heavily on agriculture, which faces numerous challenges. Meeting the current food demands of the population has become increasingly difficult due to factors such as population explosion, uneven weather conditions, and shortfall of resources. In addition to these challenges, the severity and prevalence of crop diseases have been on the rise. The presence of plant diseases significantly hampers agricultural production, exacerbating food insecurity if not addressed promptly. Continuous monitoring is essential to mitigate production losses caused by crop diseases. Precision agriculture, a rapidly evolving field, aims to tackle concerns regarding agricultural sustainability. Machine learning (ML) stands out as a promising technology in this domain, enabling machines to learn autonomously without direct programming. Numerous studies have leveraged Machine Learning methods for detection and classification of plant diseases, primarily utilizing plant or leaf images as input and categorizing them as healthy or diseased, or performing multiclass classification for multiple diseases. Machine learning (ML) techniques such as Random Forest and Deep Learning (DL) have been commonly used for this purpose. However, fewer studies have focused on simultaneously identifying the disease type and the diseased input image regions. This aspect gains significance in scenarios with multiple plant diseases or when precise localization of diseased regions in large crop images is required. Moreover, the object detection challenge poses greater difficulty compared to classification, and DL methods struggle in uncontrolled environments, such as images with noisy backgrounds. This paper aims to review the application of ML and DL methods in either classifying or detecting plant diseases, offering insights into their efficacy within the realm of precision agriculture. Numerous research papers have explored ML and DL techniques in the context of precision agriculture, contributing to ongoing efforts to enhance agricultural productivity and sustainability.

II. Literature Review

This section offers an in-depth examination of disease detection and classification techniques employing ML and DL methodologies, as evidenced in the existing literature.

Classification

Amara et al. [1] LeNet architecture is used to classify diseases in banana leaves. In their work they downsized images to 60x60 in the pre-processing steps and converted to greyscale. This architecture achieved accuracy between 92% to 99% with plant village data set.

Cruz et al. [2] applied the LeNet architecture to detect indications of olive decline in their research. They trained the LeNet architecture network using the PlantVillage dataset, where images were pre-processed by resizing them to 256×256. Their reported accuracy reached an impressive 99%.

De Chant et al. [3] introduced a 3 stage method of employing CNN models to identify N.L.B. infected maize plants in their investigation. They curetted a bespoke dataset comprising 1,796 images and achieved an accuracy of 96.7% in their results.

The Lu et al. [4] authors presented a multistage CNN architecture, drawing inspiration from AlexNet, with the aim of detecting diseases in rice plants. To compile their dataset, they collected images from both agricultural-pest and insect-pest databases. Before analysis, the images underwent preprocessing steps, including resizing to 512 × 512 pixels and the application of the Z.C.A Whitening technique to eliminate data correlation. This model achieved a notable accuracy of 95.48%.

In their study, Oppenheim and Shani [5] harnessed the power of a CNN to categorize potatoes into five classes. Four categories are infected and one is healthy. Their dataset includes 400 images of infected potatoes captured through three digital cameras. As part of the preprocessing phase, they standardized the images by 224×224 pixels and converting them to grayscale. They achieve the accuracies ranging from 83% when trained with only 10% of the data to an impressive 96% with 90% of the data utilized for training.

Barbedo [6] identified the key factors affecting the design and efficacy of CNNs in the realm of plant disease identification. PDDB dataset having 50,000 images is used to identify corn diseases. Additionally, they conducted an investigation into nine factors influencing disease detection in maize fields. Four different datasets were used for training; achieved the highest accuracy of 87% with a subdivided dataset.

Lu et al. [7] conducted a study utilizing a high-resolution spectral sensor for the detection of tomato leaves diseases at various growth stages. They introduced the K-Nearest Neighbor (KNN) algorithm for identification of the sensor data into 4 groups: early_stage, late_stage, healthy, and asymptomatic. They used PCA to achieve 85.7% in healthy leaves and 86.4% in asymptomatic leaves, 73.5% in early stage and 77.1% for late stage leaves.

In their study, Pineda et al. [8] focused on predicting diseases caused by the bacteria Dickeyadadantii in melon leaves. Using three machine learning (ML) algorithms, namely LRA, SVM, and ANN. Their investigation demonstrating a superior accuracy of 99.1%, particularly in classifying images depicting entire leaves.

Al-Saddik et al. [9] examined spectral bands for developing a multispectral camera for UAV to detect diseased grapevine fields. The targeted disease is highly contagious, incurable, and can cause significant production losses. To identify the most effective spectral bands, 2 spectral examination methodologies were employed. One method involved a feature selection, utilizing the successive projection algorithm. The second method focused on classic vegetation metrics. SVM and discriminant classifiers were employed in this study. The accuracy of the models varied depending on the grapevine variety under consideration. The approach using the successive projection algorithm outperformed the common vegetation metrics, achieving a classification accuracy exceeding 96%.

Dhingra et al. [10] introduced methodologies aimed at identifying diseases affecting basil leaves through the application of digital image processing methods. They employed nine distinct classifiers for this purpose. The process of image acquisition involved gathering samples from an herb garden, with careful attention given to standardizing the surface condition of the leaves. The classifiers use Decision Trees (DT), Support Vector Machines (SVM), linear models, Naive Bayes, K-Nearest Neighbors (KNN), AdaBoost, discriminant analysis, Random Forests (RF), and Artificial Neural Networks (ANNs). The classification task aimed to segregate the images into two primary categories such as infected and healthy. Among the nine classifiers employed, Random Forests (RF) emerged as the most accurate, achieving an impressive exactness of 98.4%.

Habib et al. [11] introduced agro-medical expert system for the identification of papaya diseases using computer vision methods to analyze images captured through portable devices. The objective of the study was to disease detection and disease classification. They achieved a commendable accuracy rate of 90.15%.

Karthik et al. [12] introduced 2 types of Deep Neural Network (DNN) models aimed at discerning infection present in tomato leaves. One model uses residual learning atop a feed forward CNN to acquire essential features, and other model incorporated strengthened attention mechanisms and residual learning within CNNs. These models tested using the Plant Village dataset, achieving reported accuracies about 95% and 98%.

Karlekar and Seal [13] recommended a machine vision technology for identifying and categorizing leaf diseases within crops of soybean. Their approach involves isolating the leaf section by removing multifaceted backgrounds from the whole image. Subsequently, a Convolutional Neural Network (CNN) named SoyNet, trained on the PDDB dataset comprising 16 classes, classifies the segmented leaf images. During preprocessing, the images are resized to 100 × 100 pixels. Impressively, this model achieves an identification accuracy of 0.9814.

Disease Detection

Jiang et al. [14] utilized a deep learning (DL) methodology withGoogLeNet architecture to detect infections in apple leaves. Custom dataset consisting of 2029 images depicting unhealthy apple leaves and subsequently trained their algorithm to identify 5 apple leaf ailments like Alternaria leaf spot, brown spot, mosaic, grey spot, and rust. Their model achieved a commendable detection accuracy of 0.7880mAP.

Li et al. [15] introduced a methodology for disease identification in rice crops employing a convolutional neural network. They collected images using mobile phones and used Faster R-CNN as the underlying framework for image detection. Comparative analysis demonstrated that their proposed approach outperforms ResNet50 and ResNet101 in terms of accuracy and efficiency.

Saleem et al. [16] integrated three different algorithms for object detection with four feature extractors and three optimization techniques to address plant disease identification. Among these, the S.S.D model linked with the InceptionV2 feature extractor and trained using the Adam-optimizer achieving a mAP of 73.07%.

Sun et al. [17] introduced a model designed to detect maize-leaf blight infection on maize crops utilizing the S.S.D. algorithm. They employed a dataset comprising 18,000 images captured by a camera mounted on a UAV. Their model achieved an impressive accuracy of 91.83%.

Xie et al. [18] introduced a deep learning-based detector designed for identifying leaf infections in grape plants. They used disease dataset consisting of 4,449 original images and augmented it with an added 62,286 unhealthy leaf images. The model trained using data augmentation techniques. This approach resulted an accuracy of 81.1%.

Selvaraj et al. [19] introduced a pixel-based classification method integrated with machine learning (ML) models to detect banana crops using multilevel satellite images and unmanned aerial vehicles (UAVs). They utilized Random Forest (RF) for pixel-based classification and devised a mixed model strategy incorporating RetinaNet along with minimized-classifier for banana localization and infection classification using U.A.V RGB images. Their proposed method produced accuracies of 0.994, 0.928, 0.933, and 0.908 for detecting banana bunchy top disease.

III. Challenges In Plant Disease Detection

Following an extensive examination of machine learning (ML) and deep learning (DL) algorithms for plant/crop disease/infection detection and classification, many challenges in real field applications of plant disease detection have come to light.

1. Existing models are predominantly on image data, neglecting valuable non-image data such as environmental data (temperature and humidity). This oversight limits the understanding of plant health and disease dynamics. Addressing this gap by integrating nonimage data into classification and object detection algorithms is crucial for enhancing the accuracy and robustness of predictions.
2. The availability of fully annotated open datasets for plant disease research remains limited. Numerous studies heavily rely on the PlantVillage dataset, primarily acquired under controlled laboratory conditions. There's a pressing need for larger datasets collected under real-world settings to better reflect diverse environmental conditions and disease manifestations.
3. While most research approaches views disease detection as a classification problem, often binary or Multiclass, there is growing acknowledgments that object detection methods can provide more comprehensive insights by not only identifying the type of disease but also pinpointing the affected regions within the image. Object detection methodologies have the potential to facilitate more detailed analyses of plant health.
4. Researcher depends on a single dataset for both training and testing their models. Models trained on single dataset frequently exhibit subpar performance when applied to different datasets. To improve the model performance, diverse range of datasets could be used.

5. Instead of relying only on CNNs models, researcher can find neural network architectures like recurrent- neural- networks (RNN)that improves disease detection.
6. Many researchers use long leaf image data sets for analysis. They can investigate on small leaves also. That enhances the detection of disease in early stage.

IV. Future Research Scope disease Detection in Plants

Apart from the aforementioned challenges, there exist numerous promising avenues for future research in the field of plant disease detection.

1. To enhance prediction accuracy in disease detection algorithms, it's imperative to develop models that can seamlessly integrate nonimagedata, such as environmental factors. By incorporating additional contextual information beyond visual cues, these models can provide a more comprehensive understanding of the underlying factors influencing plant health. This holistic approach enables more accurate and robust predictions, thereby improving the efficacy of disease detection systems.
2. To bolster the generalizability of models in agricultural settings, it's crucial to collaborate with domain experts to create diverse and real-world datasets. By capturing data under varied environmental conditions and agricultural practices, these datasets can better reflect the complexities of real-world scenarios. This collaborative effort ensures that models are trained on a representative range of data, improving their ability to adapt and perform accurately across different agricultural contexts.
3. There's a growing need to prioritize object detection methods in plant disease prediction endeavors. By leveraging object detection techniques, researchers can glean more granular insights into disease localization within plant images. This shift in focus promises to enhance the precision and specificity of disease detection models, enabling more accurate identification of affected regions and facilitating targeted intervention strategies.
4. Developed model must be practically implementable.
5. To overcome challenges posed by variable lighting conditions and occluded images, it's crucial to implement techniques that enhance algorithm robustness. By

developing strategies specifically designed to mitigate the effects of illumination variations and image occlusions, algorithms can maintain their performance consistency across diverse environmental settings and image complexities. This proactive approach ensures that disease detection systems remain reliable and effective under real-world conditions, ultimately improving their utility in agricultural applications.

6. Efforts to enhance computational efficiency are paramount, which is necessitating a focus on optimizing model architectures and algorithms to cater to real-time applications. By streamlining computational processes and reducing resource demands, optimized models can deliver swift and responsive performance, crucial for deployment in dynamic agricultural settings. This optimization drive ensures that disease detection systems not only maintain high accuracy but also operate seamlessly in real-world scenarios, maximizing their practical utility and impact.

V. Conclusion

This study gave us insight into existing research employed utilizing machine learning (ML) and deep learning (DL) methods used for farming. This study was highlighting on methodologies for plant and crop disease detection and classification. Here, introduced a classification scheme that classifies related works into distinct classes. These studies are divided into two categories based on methodology, namely classification and object detection approaches. The review here presented an overview of available datasets for plant disease detection and classification, offering insights into their respective classes, data characteristics, and suitability for either classification or object detection tasks. This comprehensive analysis aims to provide valuable insights and guidance for researchers in farming.

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