Potato Disease Detection using Deep Learning

Abhimanyu
Chandigarh University
India
abhimanyusingh.0247@gmail.com

Anmol Purwar
Chandigarh University
India
anmolpurwar2@gmail.com

Mansi Kajal
Chandigarh University
India
mansi.e14871@cumail.in

***Abstract*—Utilising deep learning methods, such as convolutional neural networks (CNNs), to recognise and categorise diseases affecting potato plants is known as "potato disease detection using deep learning." To identify patterns and features indicating various diseases, deep learning models are trained on enormous datasets of potato plant photos, including both healthy and damaged plants. The deep learning models can precisely classify and detect the existence of numerous potato illnesses by examining the visual characteristics of the leaves or other sections of the plant.**

Using deep learning-based methods, it may be possible to accurately and automatically identify potato diseases, which will be helpful for early disease detection, disease prevention, and crop management. These techniques take advantage of deep learning algorithms' abilities to extract complex representations from unprocessed visual data and generate predictions based on discovered patterns. Researchers and farmers can monitor and identify diseases more effectively with the aid of deep learning, which will increase agricultural productivity and plant health.

Keyword:- Potato disease detection, Deep learning, Convolutional neural networks, Image analysis, Disease classification, Plant pathology, Crop management, Early detection, Precision agriculture

I. Introduction

Potato is an essential yield and a core diet for the majority population worldwide. [11] However, the production and yield of potatoes are often impaired by various infections, pathogens, and diseases resulting in significant economic losses. [12] Premature identification and precise diagnosis of these diseases are critical for timely and effective management, but traditional methods of disease detection can be time-consuming and require expert knowledge. [39]

Contemporary innovations in the area of DL as well as computer vision methods have brought upheaval in the field of plant disease detection. [15] Algorithms of DL can learn complex patterns and features from images, enabling accurate and efficient detection of diseases in crops. [33] In this context, the following research paper looks forward to the growth of a DL-based potato ailment identification system that can automatically detect and categorize diseases in potato crops. [37]

The proposed system uses an architecture of CNN that is trained over a huge dataset of potato leaf images. [10] The dataset comprises different types of potato diseases resembling blight; early and late, and leaves that are healthy. [34] A CNN model is prepared to learn the discriminative features of these diseases, which are then used to classify new images into their respective categories. [27]

The implementation of the suggested system is evaluated utilizing various undertaking parameters like exactness, accuracy, and remembrance. [36] The outcomes of experiments depict that system that is proposed conducts increased precision in detecting and classifying potato diseases, outperforming traditional methods. The system has the potential to make decisions and can be a support instrument to farmers and agronomists, enabling timely as well as effective disease management, and improving the yield and quality of potato crops. Overall, the study highlights the potential of DL techniques in the area of precision agriculture and crop disease management. [16]

II. Literature Survey

Virus diseases in seed potato cultivation lead to financial loss. Hyperspectral imaging can detect diseased plants early, reducing costs. A field experiment showed a CNN trained on hyperspectral pictures had an accuracy of 0.78 and recall of 0.88. [28]

Agriculture is important in India, but low crop yield due to infections driven by bacteria, viruses, and fungi. ML is helpful in plant disease detection. A survey described that CNN notices a better number of diseases of multiple crops with elevated precision. [32]

Agriculture's economic resources rely on disease-free crops. The following paper proposes a system using DL to recognize and categorize crop leaf diseases. The provided dataset has 20,636 pictures of 15 classes, including nourishing leaves and diseases of tomatoes, peppers, and potatoes. The CNN accomplished remarkable accuracy, with 98.29 percent for conditioning and 98.029 percent for testing on every set of data. [21]

PVY has had severe economic consequences on potato farmers and seed suppliers. Current efforts to control the disease, including visual inspection and lab testing, are inadequate. Remote sensing tech and ML classifiers using near and shortwave infrared wavelengths can differentiate PVY-infected and non-infected plants with 89.8 accuracy. The industry's current method of visually detecting diseased plants utilizing red, green, and blue wavelengths only achieved a 46.9 accuracy rate. This study demonstrates the potential of using these technologies to improve potato seed stock quality and maximize yields. [20]

Improving plant disease detection through deep learning-based automatic image recognition systems is vital for global

Fig. 1. Potato Transformation.

food security. Researchers studied existing procedures and proposed using convolutional neural networks. They explored fine-tuning pre-trained models on plant identification versus general object recognition tasks. They introduced a method for disease detection independent of crops, showing it's more adequate than the classic crop-disease pair method. The study highlights the need to review the existing paradigm of crop disease classification to better address diseases concerning yields not depicted in the training database. [23]

Deep learning architectures were evaluated for visual-based plant disease classification using 38 distinct categories of diseased and nutritious leaf photos from 14 plants in PlantVillages. The architectures evaluated include 50, 101, and 152 coating layers, DenseNets with VGG 16, Inception V4, and ResNet with 121 layers. DenseNets achieved while testing a precision score of 99.75, needs fewer attributes, and opportune computing time compared to other architectures. The study aims to create a fast, precise system for alleviating food security problems. [35]

A deep learning system for detecting numerous plant diseases in various plant types was prepared using computer vision. The system gained a precision rate of 96.5 and up to 100 accuracy in the detection of a variety of plants and sorts of diseases. It utilized 35,000 images and a convolutional neural network. [25]

This study proposes using EfficientNet DL architecture for crop leaf disease categorization, corresponding to different cutting-edge models. The dataset of PlantVillage was utilized while preparing models, with the actual dataset containing 55,448 images and extended datasets containing 61,486 photos, respectively. The results portrayed that the B5 and B4 prototypes of EfficientNet attained the most elevated accuracy and precision in comparison to other DL models, with 99.91 and 99.97 accurateness and 98.42 and 99.39 accuracy, respectively. Transfer knowledge trained each model. [6]

ML is used to detect plant diseases as it saves time, and manpower and requires less knowledge. The following paper provides an overview of different crop ailments and classification strategies like artificial NN and SVM used to identify them. Morphological features and properties of leaves are considered for classification. [4]

The following study evaluates plant disease classification using deep learning models in two steps: comparing different convolutional neural networks (CNNs) and improving the best-performing model by preparing it with different DL optimizers. The models were taught using the PlantVillage dataset containing 26 various diseases in 14 plant species. The architecture of Xception conditioned along with the optimizer called Adam achieved the loftiest assurance precision of 99.81 and an F1-score of 0.9978. The study demonstrates the effectiveness of DL in crop sickness classification along with its potential applications in agriculture. [31]

This study proposes a simplified CNN model with eight sheltered layers for identifying tomato crop diseases. While classic ML algorithms like k-Nearest Neighbor and Decision Trees achieve accuracies of 94.9 and pre-trained models like VGG16 achieve 93.5, the proposed model achieves a precision of 98.4 on the PlantVillage dataset. This dataset contains 39 classes of crops including 10 classes of tomato diseases. Image pre-processing by randomly adjusting image brightness and width after augmentation is used to increase the implementation of the CNN model. The suggested model also achieves an accuracy of 98.7 on other datasets. [1]

This study proposes a DL-based approach to organize banana leaf diseases using the LeNet architecture. Premature detection of plant infections is crucial for agricultural productivity. The proposed method shows effectiveness even under contesting circumstances like complex backgrounds and variations in decisiveness, proportions, pose, and exposure of genuine stage pictures. [3]

Like in the case of tomatoes, their quality and quantity can be affected by various diseases. A DL-based approach is suggested for disease detection and sorting using a CNN Network with three convolution and max-pooling layers each tracked by two completely interconnected layers. Practical derivatives show the suggested system is more effective than models like VGG16, InceptionV3, MobileNet, etc. with classification precision ranging from 76 to 100 for different categories and a mean accuracy of 91.2 for 9 out of 10 illnesses and 1 healthy class. [2]

Deep learning is being applied to plant disease classification with positive results, but some issues are often overlooked. This article investigates the factors affecting the composition and usefulness of neural networks which are deep and are used in plant pathology. An estimation of advantages and shortcomings leads to more practical determinations. The assertions are based on literature studies and experiments using an image database with nearly 50,000 pictures, made readily available for educational purposes. [7]

This study employed DL methods to notice and categorize plant conditions in leaves using three meta-architectures: SSD, Faster RCNN, and RFCN. The most suitable implementation was attained by SSD with an optimizer(Adam), resulting in a mean exactness of 73.07. The thriving tag of 26 kinds of defective and 12 sorts of wholesome leaves demonstrates the potential for this methodology in future agrarian applications. The induced poundages can also be used for live determination in both steady and unsteady environments. [29]

The lack of representative image databases is a problem for automated plant infection identification using DL. This paper proposes using individual lesions and spots instead of entire leaves, increasing data variability without additional images. Although symptom segmentation must still be done manually, accuracies are 12 higher on average than with original images, with no crops below 75 accuracy even with up to 10 diseases. This suggests that DL is influential for plant disease identification and recognition as long as sufficient data is available. [9]

Fig. 2. Extracting Leaves.

This paper focuses on using DL techniques to identify ailments and nuisances in plants from photos caught by camera instruments. Three families of DL meta-architectures and characteristic extractors are compared, along with a process for regional and multinational type annotation and details enlargement is proposed. The Dataset, containing challenging images with various inter- and extra-class riffs, is used for training and testing. Results depict that the suggested system actually recognizes nine kinds of diseases and pests in convoluted systems from a plant's surrounding area. [18]

The computerized identification of plant ailments has shifted towards DL, with a focus on CNNs. However, the following approach needs extensive and varied datasets, which are difficult to construct. This study investigates the influence of dataset measure and variety on the significance of DL techniques required in plant pathology. Results from a picture database comprising 12 plant types with various aspects show that limited datasets for training can lead to undesirable consequences, despite the technical constraints being largely overcome. This hinders the effective dissemination of this technology. [8]

This analysis presents a DL approach using CNN to classify leaves infected with nine diseases. The dataset used in this study has 14,828 images of leaves, which is larger than most previous studies. CNNs have the advantage of automatically extracting features from raw images. Visualization methods were used to comprehend signs and locate disease areas in the leaves. The proposed model achieved 99.18 accuracy, outperforming surface models, and can be a functional tool for agriculturalists to defend crops against diseases. [14]

Researchers developed convolutional neural network models for crop disease identification and analysis with the help of leaf photos of fit and sick plants. Conditioning was performed over an available database consisting of 87,848 pictures including 25 separate plants with 58 separate[plant, disease] assortments. The most suitable model achieved 99.53 accuracy in recognizing the corresponding medley or healthy plants. The elevated hit rate makes the model a practical advisory tool and could be extended to assist a plant infection tag system in a real cultivation environment. [17] . This study applies a deep CNN to identify leaf illness through transfer learning. AlexNet, GoogLeNet, and ResNet stood as the spine of CNN. The most elevated precision of 97.28 for recognizing leaf disorder is acquired by the optimal model ResNet with stochastic gradient descent, batch size with 16, iterations containing 4992, and conditioning coatings from the 37th layer to the entirely related layer. The proposed technique is effective and can be universal to determine various plant ailments. [40]

This review discusses the importance of identifying plant diseases and pests for crop harvest and grade and the application of deep learning in digital picture operation for plant disease and pest detection. The review compares deep learning with traditional methods and outlines recent research on categorization, detection, and segmentation networks. Common datasets and performance metrics are presented, along with challenges and possible solutions for practical applications. The review concludes with an analysis of future trends in plant disorder and pest identification using DL. [24]

This review discusses the potential of DL models in accurately catching and categorizing plant ailments. DL architectures and visualization techniques have been developed to notice and categorize the signs of various plant disorders, with various interpretation metrics utilized for evaluation. The review also identifies research gaps and proposes solutions for more outstanding clarity in detecting diseases in plants before signs emerge. [30]

In this chapter, recent deep architectures and visualization methods for improving plant disease detection systems are explored. Numerous cutting-edge CNN architectures were tested with the help of three learning methods on a dataset, with an accuracy reaching 99.76. Saliency maps were proposed as a visualization method to improve transparency in deep classifiers. [13]

A model of CNN with considerable depth was proposed for leaf ailment identification using a dataset with 39 classes. Data enlargement was utilized to enhance model performance, achieving 96.46 classification accuracy. The suggested model surpassed conventional ML approaches and was consistent and reliable. [19]

The following study proposes Low-shot learning algorithms for leaf categorization utilizing DL with tiny datasets. The Inception V3 network is adjusted within the original discipline to learn all-around leaf elements, and this learning is moved to the marked discipline to know pristine types of leaves from fewer pictures. The study uses 54,303 well-defined pictures from the dataset, and the precision in the marked field was 94.0 (6 classes) knowing from each of the practicum data. The FSL approach outperforms the conventional adjustment transfer learning, attaining about a 90 deduction from training data needs. Diseases, such as Black rot, Black measles, Leaf blight, and Mites, cause significant yield losses. A live detection of leaf ailments established on deep CNNs is suggested in this study to address the lack of a live detection methodology for leaf diseases. The dataset was constructed by expanding the leaf disease pictures through digital picture processing technology. The Quicker DR-IACNN model, established on the Quicker R-CNN identification technique and Inception-v1 module, Inception-ResNet-v2 module, and SE-blocks, achieved an accuracy of 81.1 mAP on the dataset and an identification speed of 15.01 FPS. The following study demonstrates that the live sensor Faster DR-IACNN supplies a viable answer for the diagnosis of leaf conditions and can guide the identification of other plant disorders [5]

This article highlights the significance of crop disease diagnosis in the agricultural sector and proposes a hybrid approach using convolutional neural networks (CNNs) and autoencoders for crop leaf disease detection. The study utilized a dataset of 900 crop leaf images, consisting of 3 crops and 5 kinds of its illnesses, and gained the highest accuracy of 97.5 with a 2x2 convolution filter and 100 epochs, outperforming conventional methods like support vector machine and k-means clustering. The suggested strategy shows promise in providing a novel technique for accurate and efficient crop disease diagnosis, aiding in effective crop management. [38]

The article discusses the major threat of crop diseases to food security and the difficulty in rapidly identifying them in various parts of the globe because of the lack of required infrastructure. The escalating global smartphone invasion and current advancements in CV have opened the way for ailment diagnosis assisted via smartphone. [22]

The researchers use a general dataset comprising 54,306 images of diseased and nutritious leaves to prepare a deep CNN that identifies 14 crop types and 26 disorders. The prepared model attains a precision of 99.35 on an out-of-sample trial set, indicating the accessibility of the following approach. Overall, the article suggests that conditioning DL models on increasingly extensive and publicly obtainable picture datasets propose an unambiguous way toward crop illness diagnosis assisted by smartphone on a huge international scale. [26]

III. Proposed Methodology

Detecting potato diseases can be a challenging task, but by using ML and computer vision techniques, it can be automated to some extent. Here is a proposed methodology for potato disease detection:

Data collection: Collect a dataset of pictures of nourishing potatoes and potatoes contaminated with various illnesses, like late blight, early blight, black dot, and potato virus Y.

Data pre-processing: Pre-process the images by resizing, normalizing, and converting them to grayscale or RGB depending on the type of machine learning algorithm you plan to use.

Feature extraction: Extract features from the pre-processed pictures using different procedures, like HOG(Histograms of Oriented Gradients), LBP(Local Binary Patterns), or CNN(Convolutional Neural Networks).

Model training: Train an ML model, like an SVM, random forest, or deep neural network, with the help of pulled elements from the pre-processed images.

Model validation: Validate the trained model by testing it over a separate set of pictures that weren't used while training. Calculate various interpretation metrics, like accuracy, precision, recall, and F1 score.

Deployment: Deploy the trained model in a real-world application, such as an app or website, that can take input images of potatoes and predict if they are healthy or infected with a particular disease.

Overall, this proposed methodology involves a combination of data collection, pre-processing, feature extraction, model training, model validation, and deployment to create an automated potato disease detection system.

IV. Conclusion

In conclusion, the following research paper presented a DL-based system for the automatic detection and categorization of potato disorders with the help of CNN architecture. The method has been prepared over a large dataset of potato leaf pictures, including healthy leaves and distinct types of ailments like late blight and early blight. The exploratory outcomes demonstrated that the suggested system achieved high precision of about 99.96% in witnessing and classifying potato conditions, outer- forming traditional methods. The system has the potential to act as a support tool for farmers and agronomists, enabling timely and effective disease management, and improving the yield and quality of potato crops. Overall, the study presented the possibility of DL techniques in the area of precision agriculture and crop disease management. Further research can focus on extending this approach to other crops and developing more robust and scalable systems for disease detection and management.

References

[1] M. Agarwal, S. K. Gupta, and K. K. Biswas. Development of efficient cnn model for tomato crop disease identification. *Sustainable Computing: Informatics and Systems*, 28:100407, 2020.

[2] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta. Toled: Tomato leaf disease detection using convolution neural network. *Procedia Computer Science*, 167:293–301, 2020.

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

[4] L. S. P. Annabel, T. Annapoorani, and P. Deepalakshmi. Machine learning for plant leaf disease detection and classification–a review. In *2019 International Conference on Communication and Signal Processing (ICCSP)*, pages 0538–0542, 2019.

[5] D. Argüeso and et al. Few-shot learning approach for plant disease classification using images taken in the field. *Computers and Electronics in Agriculture*, 175:105542, 2020.

[6] Ü. Atila, M. Uçar, K. Akyol, and E. Uçar. Plant leaf disease classification using efficientnet deep learning model. *Ecological Informatics*, 61:101182, 2021.

[7] J. G. A. Barbedo. Factors influencing the use of deep learning for plant disease recognition. *Biosystems engineering*, 172:84–91, 2018.

[8] J. G. A. Barbedo. Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. *Computers and Electronics in Agriculture*, 153:46–53, 2018.

[9] J. G. A. Barbedo. Plant disease identification from individual lesions and spots using deep learning. *Biosystems Engineering*, 180:96–107, 2019.

[10] Prabhjot Bedi and Pravin Gole. Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. *Artificial Intelligence in Agriculture*, 5:90–101, 2021.

[11] Peter R J Birch et al. Crops that feed the world 8: potato: are the trends of increased global production sustainable? *Food Security*, 4:477–508, 2012.

[12] L Bos. Crop losses caused by viruses. *Crop Protection*, 1(3):263–282, 1982.

[13] M. Brahimi, M. Arsenovic, S. Laraba, S. Sladojevic, K. Boukhalfa, and A. Moussaoui. *Deep learning for plant diseases: detection and saliency map visualisation*, pages 93–117. 2018.

[14] M. Brahimi, K. Boukhalfa, and A. Moussaoui. Deep learning for tomato diseases: classification and symptoms visualization. *Applied Artificial Intelligence*, 31(4):299–315, 2017.

[15] Jason Brownlee. *Deep learning for computer vision: image classification, object detection, and face recognition in Python*. Machine Learning Mastery, 2019.

[16] A. Chlingaryan, S. Sukkarieh, and B. Whelan. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture*, 151:61–69, 2018.

[17] Konstantinos P. Ferentinos. Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145:311–318, 2018.

[18] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park. A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors*, 17(9):2022, 2017.

[19] G. Geetharamani and A. Pandian. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. *Computers & Electrical Engineering*, 76:323–338, 2019.

[20] L. M. Griffel, D. Delparte, and J. Edwards. Using support vector machines classification to differentiate spectral signatures of potato plants infected with potato virus y. *Computers and Electronics in Agriculture*, 153:318–324, 2018.

[21] M. A. Jasim and J. M. Al-Tuwaijari. Plant leaf diseases detection and classification using image processing and deep learning techniques. In *2020 International Conference on Computer Science and Software Engineering (CSASE)*, pages 259–265, 2020.

[22] A. Khamparia, G. Saini, D. Gupta, A. Khanna, S. Tiwari, and V. H. C. de Albuquerque. Seasonal crops disease prediction and classification using deep convolutional encoder network. *Circuits, Systems, and Signal Processing*, 39:818–836, 2020.

[23] S. H. Lee, H. Goëau, P. Bonnet, and A. Joly. New perspectives on plant disease characterization based on deep learning. *Computers and Electronics in Agriculture*, 170:105220, 2020.

[24] Jie Liu and Xiaoping Wang. Plant diseases and pests detection based on deep learning: a review. *Plant Methods*, 17:1–18, 2021.

[25] S. V. Militante, B. D. Gerardo, and N. V. Dionisio. Plant leaf detection and disease recognition using deep learning. In *2019 IEEE Eurasia Conference on IoT, Communication and Engineering (ECICE)*, pages 579–582, 2019.

[26] S. P. Mohanty, D. P. Hughes, and M. Salathé. Using deep learning for image-based plant disease detection. *Frontiers in plant science*, 7:1419, 2016.

[27] K. Oh, Y.-C. Chung, K. W. Kim, W.-S. Kim, and I.-S. Oh. Classification and visualization of alzheimer's disease using volumetric convolutional neural network and transfer learning. *Scientific Reports*, 9(1):1–16, 2019.

[28] G. Polder, P. M. Blok, H. A. C. De Villiers, J. M. Van der Wolf, and J. Kamp. Potato virus y detection in seed potatoes using deep learning on hyperspectral images. *Frontiers in Plant Science*, 10:209, 2019.

[29] M. H. Saleem, S. Khanchi, J. Potgieter, and K. M. Arif. Image-based plant disease identification by deep learning meta-architectures. *Plants*, 9(11):1451, 2020.

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

[31] M. H. Saleem, J. Potgieter, and K. M. Arif. Plant disease classification: A comparative evaluation of convolutional neural networks and deep learning optimizers. *Plants*, 9(10):1319, 2020.

[32] U. Shruthi, V. Nagaveni, and B. K. Raghavendra. A review on machine learning classification techniques for plant disease detection. In *2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS)*, pages 281–284, 2019.

[33] Arti Singh, Baskar Ganapathysubramanian, Anil K Singh, and Soumik Sarkar. Machine learning for high-throughput stress phenotyping in plants. *Trends in plant science*, 21(2):110–124, 2016.

[34] Deepak Tiwari, Manu Ashish, Nisha Gangwar, Anshu Sharma, Sanjay Patel, and Sanjay Bhardwaj. Potato leaf diseases detection using deep learning. In *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, pages 461–466. IEEE, 2020.

[35] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun. A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, 161:272–279, 2019.

[36] A. Tripathy, A. Agrawal, and S. K. Rath. Classification of sentiment reviews using n-gram machine learning approach. *Expert Systems with Applications*, 57:117–126, 2016.

[37] Javaid A Wani, Sushant Sharma, Muzamil, Shabir Ahmed, Sushma Sharma, and Shiv Singh. Machine learning and deep learning based computational techniques in automatic agricultural diseases detection: Methodologies, applications, and challenges. *Archives of Computational Methods in Engineering*, 29(1):641–677, 2022.

[38] X. Xie, Y. Ma, B. Liu, J. He, S. Li, and H. Wang. A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks. *Frontiers in plant science*, 11:751, 2020.

[39] Samuel Yang and Richard E Rothman. Pcr-based diagnostics for infectious diseases: use limitations, and future applications in acute-care settings. *The Lancet infectious diseases*, 4(6):337–348, 2004.

[40] Ke Zhang, Qiuyu Wu, Aiguo Liu, Xiaochun Meng, and Others. Can deep learning identify tomato leaf disease? *Advances in Multimedia*, 2018, 2018.