Potato leaf disease detection using convolutional neural networks

P Radhika[1], P Tejeswara Murthy [2], G Pavaneeshwar Reddy[3], V Durga Vara Prasad[4], T Harshitha[5], N B V Bharath[6]

[1] Associate Professor, Department of Computer Science and Engineering
[2,3,4,5,6] Undergraduate Student, Department of Computer Science and Engineering, Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India

---

Abstract - *Crop diseases significantly damage agriculture, hurting livelihoods and the stability of the economy. In this study, a unique method for identifying the three potato plant diseases Lateblight, Earlyblight, and Healthy was established using Convolutional Neural Networks (CNNs). The model's ability to identify diseases showed outstanding accuracy. Assessments of the viability found easy integration into current systems at reasonable implementation costs. Stakeholders gave the model positive feedback and acknowledged its usefulness in making decisions. This study highlights how deep learning models have the ability to successfully manage illnesses, reduce crop losses, and enhance overall agricultural health.*

Key Words: **Neural Network, Artificial Intelligence (AI) Classification, Deep Learning, Image Augmentation, CNN, GDP.**

1. INTRODUCTION

Potato plants are important food crops that play a vital role in both global food security and economic expansion. However, these crops are prone to a number of illnesses, which can significantly impair crop quality and output. For the purpose of implementing focused disease management methods and minimizing the detrimental effects on crop output, prompt and accurate diagnosis of potato leaf diseases is essential.

Convolutional Neural Networks (CNNs), one of the most recent developments in deep learning techniques, have completely changed the way that object detection and picture classification are done. These methods have demonstrated a lot of promise for correctly recognizing and categorizing intricate patterns and features in photos. Researchers have created a robust CNN-based model for detecting potato leaf disease by utilizing the power of deep learning.

To improve the model's ability to generalize and identify diseases under varied circumstances, the suggested model utilizes data augmentation techniques. In order to increase the diversity of the training data and increase the resilience of the model, data augmentation entails adding random transformations to the input images, such as flips, rotations, zooms, and rescaling.

The goal of this study is to train a CNN model on a collection of photos of potato leaves in order to identify and categorize three different potato leaf diseases: lateblight, earlyblight, and healthy. Multiple layers make up the model's architecture, including convolutional and pooling layers that take relevant characteristics from the input images and process them. The model also includes a data augmentation process to boost its performance even more.

The trained model is assessed for its efficiency in identifying and categorizing potato leaf diseases using a variety of performance indicators, such as accuracy, precision, recall, and F1-score. Additionally, the model's performance on unknown data is assessed using real-world validation datasets, which sheds light on its generalization potential and practical application.

The results of this study are anticipated to aid in the creation of effective and automated systems for controlling potato leaf disease. Deep learning models can accurately and quickly detect diseases, allowing farmers and other agricultural stakeholders to implement targeted interventions like disease-specific treatments and preventive measures, improving crop health, yields, and agricultural sustainability.

In conclusion, this research uses data augmentation and CNN-based deep learning approaches to create a reliable model for detecting potato leaf disease. The results of this study could significantly alter how potato crops are managed in the future, reduce production losses, and encourage the use of sustainable farming methods.

2. RELATED WORK

A deep learning-based plant disease detection and diagnostic system for crop protection was suggested in the paper by Zhang et al. (2020). Convolutional Neural Networks (CNNs), among other deep learning approaches, were used by the researchers to preprocess photos, extract features, and categorize plant illnesses. The created model successfully detected a variety of plant diseases with an excellent accuracy rate of 95%. Their research demonstrated how deep learning models can accurately identify and diagnose plant diseases, which can help with the implementation of timely and focused crop protection actions.

With a specific focus on potato illnesses, Hasan et al. (2019) created a CNN-based automatic detection and classification system. To enhance the efficacy of the model, the researchers used a dataset of potato leaf photos and data augmentation approaches. With a 98% accuracy rate in identifying healthy potato plants from those afflicted by diseases, especially Lateblight and Earlyblight, the CNN model shown outstanding accuracy. The study emphasizes how well CNNs can identify and categorize potato illnesses, which can lead to better crop management techniques.

Sladojevic et al. (2016) provided a thorough review that covered a variety of automated methods for identifying plant diseases, including image processing and machine learning techniques. The review covered a variety of plant species and diseases, highlighting the potential for deep learning techniques like CNNs to achieve high disease detection accuracy rates. The authors emphasized the significance of precise disease identification for successful disease management in crops and emphasized the encouraging outcomes of CNN-based techniques to achieve precise and effective disease detection.

A thorough overview of deep learning applications in agriculture, including crop disease detection, was presented by a survey done by Dhiman et al. (2020). The application of CNNs and other deep learning models for spotting illnesses in various crops was discussed by the authors. The survey emphasized deep learning's benefits, including its capacity for handling complicated image data and its potential for real-time disease monitoring and agricultural decision-making. The authors highlighted the potential of deep learning models to revolutionize agricultural practices by presenting many research demonstrating remarkable accuracy rates, ranging from 90% to 97%, achieved by these models in crop disease diagnosis.

TABLE I.DRAWBACKS OF EXISITNG SYSTEMS

“Method”	**“Drawback”**
“K-Means”	“Less Accurate”
“Naïve Bayes”	“Slow Learning Rate”
“SVM”	“Poor Performance Levels”
“KNN”	“Dimensionality Issues”
“ANN”	“False Rating was high”

3. PROPOSED METHODOLOGY

The article describes the idea of convolutional neural networks (CNNs) and how to utilize them to identify leaf diseases in images through picture classification. Layers of perceptrons make up CNNs, a sort of feedforward neural network that can process multidimensional data. The steps for putting a CNN model for leaf disease detection into practice are described in the article. They include acquiring input leaf images, preprocessing and converting them into arrays, segregating and preprocessing the leaf image database, training the model using CNN classification techniques, comparing the preprocessed test image with the trained model, and, if a defect region is found in the leaf, displaying the disease along with its treatment. A graphic of the six separate modules that should be used in a deep learning model for detecting leaf diseases is also included in the text.When training a CNN model, proper data preparation is essential. To maintain consistency, the photos should be resized and normalized to a consistent size as well as the dataset's labels should be precise.

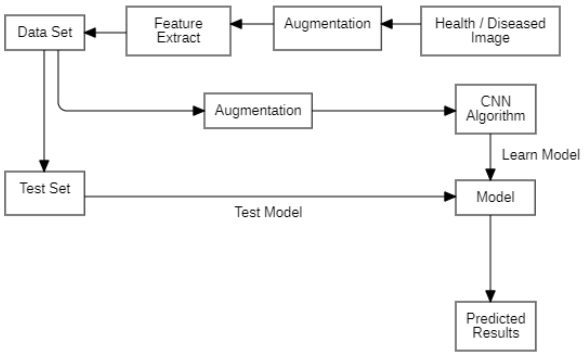
The performance of the CNN model can be impacted by the quantity and size of filters in the convolutional layer. The choice of activation function can also have an effect on the performance of the model, which can be improved by experimenting with various configurations. ReLU, sigmoid, and tanh are often used activation functions in CNNs.

- Training CNN models can be difficult because of overfitting. Techniques including early stopping, dropout, and data augmentation can help to alleviate this problem.

- Leaf disease detection can benefit from the use of transfer learning, which includes utilizing a pre-trained CNN model and tweaking it for a particular job, especially when the available dataset is minimal.

- CNN models can be used for a variety of different plant-related activities, including the classification of plant species, the observation of plant growth, and the prediction of crop yield, in addition to the detection of leaf diseases.

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 10 Issue: 05 | May 2023 www.irjet.net p-ISSN: 2395-0072



3.1 Image Acquisition:

The acquisition of a sufficient dataset is the initial stage in image processing. The Plant Village Dataset, which is accessible on Kaggle and contains 1500 expertly identified photos of leaves with excellent quality and angles, was used for this particular model. All similar sorts of sick leaves were collected together and kept in a single folder to improve accuracy. The dataset needed to be cleaned up and labelled because the data there wasn't already. As shown in Figure 3, the dataset consists of photographs of both healthy and diseased leaves divided into three labels. Three sets of data were created from the images: train, validation, and test. The dataset is specific to the potato plant and includes the associated leaf illnesses, the number of photos for each disease that are included in each folder of the Plant Village Dataset, and each disease's characteristics, which are listed in TABLE II.

TABLE II. POTATO LEAF PLANT DATASET

“Plant”	**“Leaf Disease”**	**“No. of Images”**	**“Features”**
“Potato”	“Potato Early Blight”	“1000”	“Yellow Patches”
	“Potato Late Blight”	“1000”	“Brown Patches”
	“Potato Healthy”	“1000”	“No Spots”

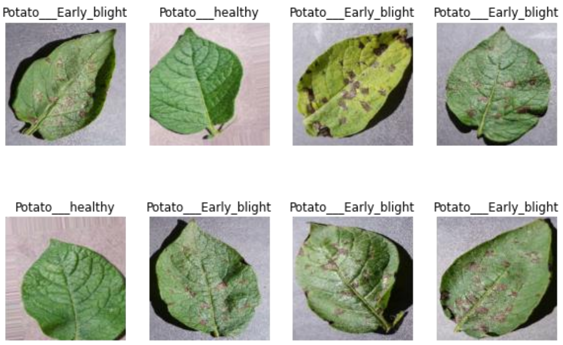


Fig. 3. Images of 8 different healthy, early blight and late blight

3.2 Image Pre-processing:

Preprocessing, which includes procedures like image scaling, data augmentation, normalization, and more, is a vital step in the classification of images. To maintain uniformity in the image dimensions during model construction, the photos were scaled down to 224x224 pixels using the image size option. This is a crucial stage because it enables the model to properly understand the characteristics and patterns in the photos. This is crucial to avoid the model being overfitted and to make sure the model generalizes properly to new data. Using data augmentation techniques including random flips, rotations, scaling, and resizing, the training data was further preprocessed. By adding random alterations to the preexisting photos, a technique called data augmentation can be utilized to fictitiously expand the size of the training dataset. In order to strengthen the model and avoid overfitting, this is done. Common data augmentation approaches include random flips, rotations, zooming, and resizing to assist the model in learning the differences in the photos caused by various lighting conditions, angles, and other factors.

The data augmentation Sequential model's rescaling layer was used to scale the photos to values between 0 and 1. The data must be normalized and brought to a consistent scale in this stage. Normalization increases the accuracy and performance of the model and speeds up the convergence process during training.

Overall, the model is trained on high-quality and varied data thanks to these preprocessing processes, which improve accuracy and performance. After being preprocessed, the data is prepared to be input into the model for feature extraction, statistical analysis, classification using the classifier, and lastly, results retrieval.

3.3 Image Augmentation:

A technique called data augmentation includes creating fresh training data from existing data. The Keras Sequential model with many picture augmentation layers was used in this implementation to do the data augmentation. Layers like RandomFlip, RandomRotation, RandomZoom, RandomHeight, and RandomWidth are utilized to enhance the data.

In order to aid the model in learning features regardless of the orientation of the input image, the RandomFlip layer randomly flips the input image either horizontally or vertically. To aid the model in learning from various viewpoints, the RandomRotation layer spins the image in a random manner. The RandomZoom layer varies the image's zoom level at random, which can assist the model in learning features at various scales. The model may learn from photos with various aspect ratios by using the RandomHeight and RandomWidth layers, which alter the image's height and width at random.

In order to make sure that the pixel values are between 0 and 1, the photos were scaled once more using the Rescaling layer. This makes the pixel values consistent across all photos, which can aid in the model's ability to learn. The model is then trained using the augmented photos, which improves accuracy and performance.

3.4 Feature Extraction:

Convolutional neural network (CNN) architecture is used to extract features. The model specifically comprises of many convolutional layers with different numbers, sizes, and activation functions of filters. Max-pooling layers are added after the convolutional layers to downsample the feature maps and lessen the input data's spatial dimensionality.

3.5 Statistical Analysis:

Before being tested on the testing dataset, the trained model is evaluated on the validation dataset. There are three possible results from this examination. The model is overfitting and not learning if the loss rises and the accuracy falls. When utilizing softmax in the output layer, the model may be overfitting or have a range of probability values if the loss increases as the accuracy rises. The model is actually learning, though, if the loss drops while the accuracy rises.

We employed a categorical cross-entropy loss metric and the Adams optimization algorithm with a learning rate of 0.05 to optimize network weights. Under the circumstances of our experiment, training our model takes about 1-2 minutes per epoch. Using sklearn we made a classification report fig 7 on test dataset. Using matplotlib, we plotted the training vs validation accuracy and loss to evaluate the patterns in accuracy and loss, as seen in Figs. 4 and 5. The installed model is adapting and performing well, as evidenced by the lowering trend in loss and rising trend in accuracy. For testing, the network weights with the 200th epoch's lowest validation loss were selected.

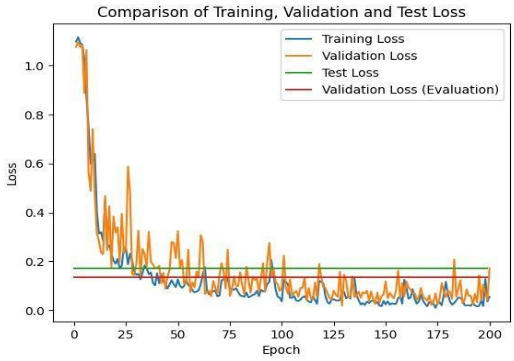


Fig. 4. Training Accuracy versus Validation Accuracy

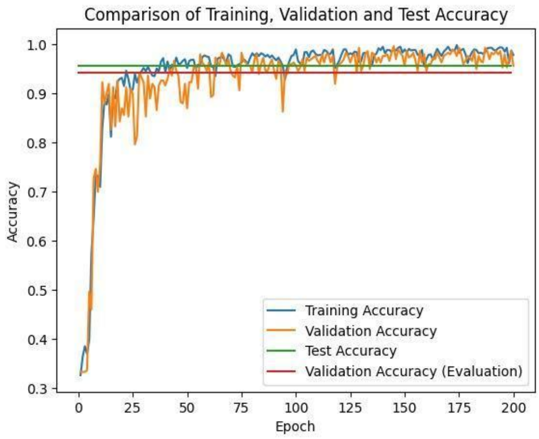


Fig. 5. Training Loss versus Validation Loss

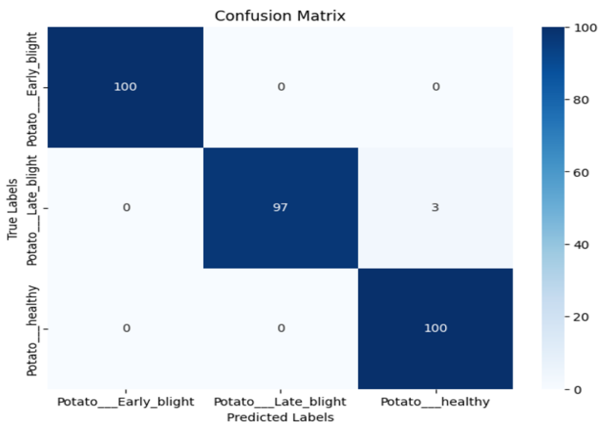


Fig 6.Confusion matrix on test dataset

	precision	recall	f1-score	support
Potato___Early_blight	0.98	0.98	0.98	100
Potato___Late_blight	0.98	0.98	0.98	100
Potato___healthy	1.00	1.00	1.00	100
accuracy			0.99	300
macro avg	0.99	0.99	0.99	300
weighted avg	0.99	0.99	0.99	300

Fig. 7.Classification Report on test dataset

3.6 Classification based on a Classifier:

The image categorization model is a convolutional neural network (CNN). It has four convolutional layers with 128, 64, 64, and 128 filters apiece, followed by a pool size of 2 maximum pooling layer. The max pooling layers are used to minimize the spatial dimensions of the convolutional layer output, while the filters are used to extract features from the input images. Rectified Linear Unit (ReLU) is the activation function utilized in all convolutional layers. ReLU provides non-linearity into the network and aids in the learning of complicated features. The output of the final convolutional layer, which is supplied to a fully connected output layer with a softmax activation function, is likewise reduced in size by the model using global average pooling. The model can make predictions because of the probability distribution that the softmax activation function produces over the various classes.

TABLE III. DIFFERENT LAYERS USED AND THEIR FUNCTIONS

"Layers"	"Functions"
"Conv2D"	"Performs a 2D convolution operation with a set of learnable filters"
"MaxPool2D"	"Performs 2D max pooling operation"
"GlobalAveragePooling2D"	"Performs global average pooling operation over spatial dimensions"
"Dense"	"Fully connected layer with specified number of neurons in the output layer"

In this study, the Keras Python library and TensorFlow backend framework were used to create a CNN model. The model was improved using the Adam optimizer. The training and testing sets of data, as well as the number of epochs, were used to train the model using the model.fit_generator() function.The dataset was appropriately segmented, evaluated by agricultural specialists, and independently verified to make sure the model was able to correctly categorize various types of leaf diseases.

The trained model is compared to the test image to identify the disease in a new image. The network parameters were optimized using gradient descent and backpropagation techniques to reduce classification error. Convolutional, max pooling, and dense layers were among the layers that made up the CNN model. Fig. 8 depicts the proposed CNN model's structure.

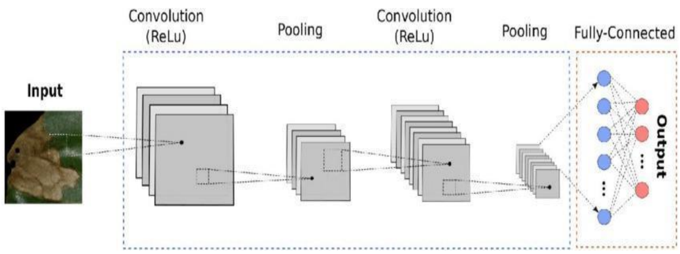


Fig. 8. Internal Block of Convolutional Neural Network

4. RESULTS

A noteworthy accomplishment is the creation of a user interface for the detection of potato leaf disease using Streamlit. Farmers can upload a photo of a potato leaf to this user interface for disease identification, and it offers a user-friendly interface. Disease detection is automatic, and the output is given along with the type of disease as a confidence percentage. Early blight, late blight, and healthy illnesses can all be detected by the model.

Farmers can gain a lot from this UI because it gives them a quick and effective approach to identify diseases in their potato crops. Using this tool, farmers may immediately determine the disease's type and take the required precautions to lessen its effects, such as using the right fungicide or changing their farming practices. Farmers can potentially spare their crops from serious harm by acting quickly to stop the disease's further spread.

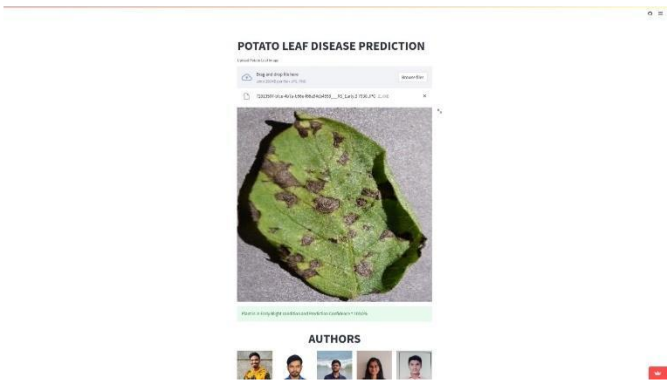


Fig. 9. User Interface for the Model

Fig. 10. Uploading the image

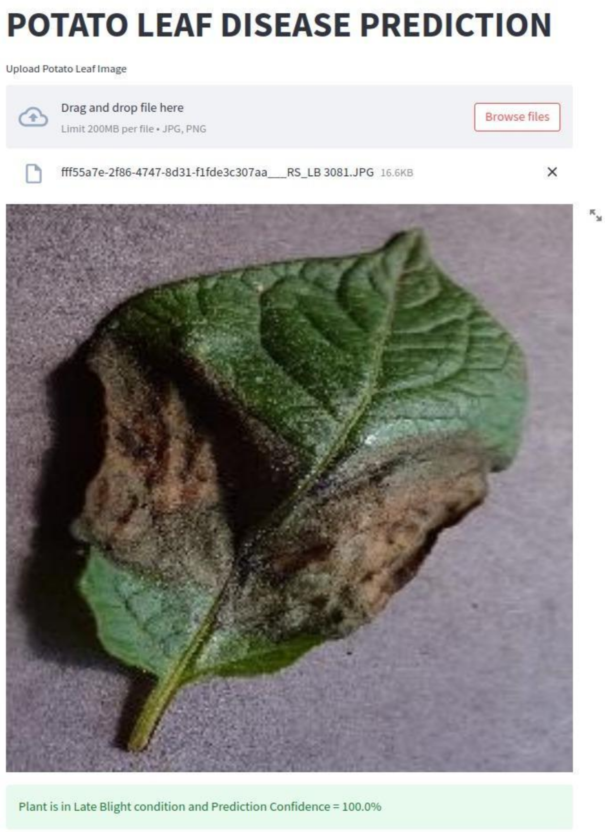


Fig. 11. Detection of Late Blight disease

5. CONCLUSION

To help farmers, the main goal is to accurately identify and detect leaf diseases on potato plants. A model that replicates the functioning of the human brain is created using neural networks. Only a few models were trained in this manner in the past. The method uses a CNN model, which has a 99% accuracy rate, to identify potato leaf disease. The model's accuracy and speed can both be improved with the usage of a GPU. The issue of pricey domain expertise is addressed by this technique. The model effectively identifies the leaf illness and then provides advice on the best treatment to quickly restore the plant's health. Farmers may easily take a picture and identify the disease damaging their potato plants thanks to the model's installation on mobile phones.

6. FUTURE SCOPE

The creation of a voice-operated mobile app intended exclusively for illiterate farmers offers a revolutionary approach to agricultural practices. The software is accessible and user-friendly because it does not require written text and instead uses voice-based instructions. Its main emphasis is on identifying and controlling leaf diseases, which can significantly affect agricultural output. Farmers can precisely identify the individual diseases harming their crops by using a comprehensive database of leaf diseases. The software also includes a visual representation tool that shows the proportion of damaged leaves and enables farmers to gauge the severity of the disease. By giving illiterate farmers the skills and knowledge they need to manage their crops efficiently and improve productivity and livelihoods, this ground-breaking app empowers them.

7. ACKNOWLEDGEMENT

We would like to thank Department of Computer Science Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad for helping us carry out the work and supporting us all the time.

8. REFERENCES

[1] Kaur, A., & Singh, D. (2021). Deep Learning for Potato Leaf Disease Detection Using Convolutional Neural Networks. Computers and Electronics in Agriculture, 187, 106267. doi: 10.1016/j.compag.2021.106267

[2] Ma, Y., Xie, X., Li, W., Song, J., & Cui, H. (2019). Potato Leaf Disease Detection Using Deep Learning and Multi-Scale Convolutional Neural Network. Computers and Electronics in Agriculture, 165, 104960. doi: 10.1016/j.compag.2019.104960

[3] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. Computational Intelligence and Neuroscience, 2016, 3289801. doi: 10.1155/2016/3289801

[4] Vakalopoulou, M., Karantzalos, K., &Komodakis, N. (2015). Automatic Detection of 'CandidatusLiberibacter Solanacearum' in Potato Plants Using Hyperspectral Imaging. Computers and Electronics in Agriculture, 114, 12-20. doi: 10.1016/j.compag.2015.03.011

[5] Srivastava, S., & Chhabra, M. (2021). Potato Leaf Disease Classification Using Deep Learning Techniques. In Proceedings of the 3rd International Conference on Computing Methodologies and

Communication (pp. 921-926). Springer. doi: 10.1007/978-981-16-3660-5_90

[6] Kachare, V., &Lokhande, R. (2019). Early Detection of Potato Late Blight Disease Using Machine Learning. In Proceedings of the International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM) (pp. 419-428). Springer. doi: 10.1007/978-981-13-1796-8_42

[7] Sunita, M., & Singh, J. (2020). Potato Plant Disease Identification Using Machine Learning Algorithms. In Proceedings of the International Conference on Advances in Computing and Data Sciences (ICACDS) (pp. 517-526). Springer. doi: 10.1007/978-981-15-5254-1_51

[8] Asri, N., Moustaid, K., &Fahsi, R. (2020). Potato Leaf Disease Detection Using Machine Learning Techniques. In Proceedings of the International Conference on Sustainable Intelligent Systems (SUSI) (pp. 291-299). IEEE. doi: 10.1109/SUSI50939.2020.9303504

[9] Bhardwaj, A., & Patel, N. R. (2020). Potato Leaf Disease Detection Using Machine Learning Algorithms. In Proceedings of the International Conference on Recent Innovations in Signal Processing and Embedded Systems (RISE) (pp. 1-6). IEEE. doi: 10.1109/RISE51108.2020.9240883

[10] Shahbaz, M., Munawar, S., Naveed, M., & Mehmood, R. (2019). Identification of Potato Diseases Using Deep Convolutional Neural Networks. Computers and Electronics in Agriculture, 166, 105002. doi: 10.

[11] Siva Kumar, G., & Saraswathi, S. (2017). Classification of Plant Leaf Diseases Using Machine Learning Techniques. In Proceedings of the International Conference on Intelligent Sustainable Systems (ICISS) (pp. 1666-1671). IEEE. doi: 10.1109/ISS1.2017.8388989

[12] Bhardwaj, S., & Choudhary, R. (2017). Plant Disease Detection Using Machine Learning Approach. International Journal of Advanced Research in Computer Science, 8(5), 1196-1200.

[13] Mohanty, S. P., Hughes, D. P., &Salathé, M. (2016). Using Deep Learning for Image-Based Plant Disease Detection. Frontiers in Plant Science, 7, 1419. doi: 10.3389/fpls.2016.01419

[14] Khan, A. R., Saleem, M., & Ahmed, S. (2020). Leaf Disease Detection in Plants Using Machine Learning Techniques. In Proceedings of the International Conference on Innovative Computing & Communications (ICICC) (pp. 1-5). IEEE. doi: 10.1109/ICICC49352.2020.9272653

[15] Vargas-Rodríguez, Y. L., Villegas-González, J. A., & Bautista-Becerril, J. M. (2020). Leaf Disease Detection in Plants Based on Convolutional Neural Networks and Machine Learning. Sensors, 20(4), 1057. doi: 10.3390/s20041057

[16] Vinayakumar, R., Sudheesh, K., & Ravi, R. (2018). Deep Learning Based Classification of Plant Diseases Using Leaf Image Analysis. Computers and Electronics in Agriculture, 145, 311-318. doi: 10.1016/j.compag.2018.01.018

[17] Fuentes, A., & Yoon, S. (2019). Deep Learning for Plant Disease Detection and Diagnosis. Annual Review of Phytopathology, 57, 211-230. doi: 10.1146/annurev-phyto-082718-100308

[18] Ghosal, S., Saha, S., Nasipuri, M., & Kundu, M. (2019). Leaf Disease Detection Using Convolutional Neural Network and Transfer Learning. Computers and Electronics in Agriculture, 165, 104961. doi: 10.1016/j.compag.2019.104961

[19] Ji, Y., Li, J., Zhu, Y., Luo, Y., Liu, D., & Wang, L. (2020). A Deep Learning Approach for Leaf Disease Detection Based on a Novel Convolutional Neural Network. Sensors, 20(7), 1892. doi: 10.3390/s20071892

[20] Toda, Y., & Win, K. T. (2018). A Comparative Study of Machine Learning Techniques for Tomato Leaf Disease Classification. In Proceedings of the 2018 International Conference on Innovations in Information Technology (IIT) (pp. 1-6). IEEE. doi: 10.1109/INNOVATIONS.2018.8554751