IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 2, July 2024

An Improve Method for Plant Leaf Disease Detection and Classification using Deep Learning

Jeetendra Mahor[1] and Ashish Gupta[2]

PG Research Scholar, Computer Science and Engineering [1]

Associate Professor, Computer Science and Engineering[2]

Nagaji Institute of Technology & Management, Gwalior, India

Abstract: *In countries like India, whose important occupation is agriculture, face a huge loss when the crops get affected by any type of disease. These diseases attack the crops in various stages and can destroy the entire production. Since most diseases are transmitted from one crop to another there is an essential requirement to detect the type of disease in the early stage so that farmers can take the required action to "save the crops" and production. Early disease detection is one of the essential activities for enhancing agricultural productivity. Diseases spread very quickly in the parts of the leaves that affect the growth of the plants. Early detection is a challenging task as the symptoms are mild for accurate identification. This research paper presents an enhanced CNN based MCC-ECNN model with fine-tuned hyper-parameters and various batch sizes for accurate plant leaf disease classification.*

Keywords: Image classification, Plant Disease Detection, image Segmentation, deep learning, CNN

I. INTRODUCTION

The mother of all countries is agriculture. The goal of agricultural research is to increase product quality and quantity while spending less money and making more money. Plant diseases may cause the quality of agricultural goods to decline. Pathogens, such as fungus, bacteria, and viruses, are what cause these diseases. As a result, it is important to identify and categorise plant diseases as early as possible. Farmers need professionals to check them constantly, but this might be excessively expensive and time-consuming. Numerous solutions have been developed, depending on the applications, to overcome or at least mitigate the issues by utilising image processing and some automatic categorization techniques.

II. RELATED WORK

Plant diseases and pests are important factors determining the yield and quality of plants. Hence it is very essential to detect plant diseases for early treatment thereby reducing its impact on productivity. In recent years, deep learning has made breakthroughs for sustainable agriculture by means of precision farming, crop protection, water management and much more.This paper presents a detailed survey of existing literature on classification and prediction of plant disease using Machine Learning and Deep Learning techniques.Sladojevic S et al. (2016) jointly developed a deep CNN model and a CaffeNet architecture for plant leaf disease classification. The CaffeNet is a transfer learning model which that is a modified version of the Alexnet architecture. The author used thirteen classes of plant leaf images. To reduce the overfitting, the images are augmented into 40000 images out of 30880 images that were used for training and 2589 images for validation. The model finally achieved 96.3 percent accuracy after fine-tuning. Mohanty et al. (2016) make use of the plant village dataset which consists of 38 classes of images and the images are both colored and grayscale. The author used both images for training and testing. They tried both the scratch and transfer learning models. AlexNet and GoogLeNet are the pre-trained architectures that were used to classify plant leaf diseases. The highest accuracy achieved was 99.34% through the transfer learning of GoogleNet on colored images with an 80-20 training-test distribution. Lu et al. (2017) proposed an AlexNet scratch CNN architecture for the classification of rice diseases. They captured 500 images in rice fields to build their own dataset for training and testing purposes. In the deep model, 10 cross- fold validation were used and the model achieved 95.4 % accuracy. Ferentinos et al. (2018) proposed a pre-trained model of CNN architectures like AlexNet, AlexNetOWTBn, GoogleNet, Overfeat, and VGG that are

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, July 2024

implemented in this work. They took nearly 59 distinct classes of plant leaf images. The author eliminated the segmentation process in the CNN model. Among the pre-trained model, the VGG network has achieved the highest accuracy of 99.53%. Kaushik M et al. (2020) proposed the Resnet50 architecture for identifying tomato leaf diseases. The author used the augmentation process to increase the size of the available data set four times (from a set of 9801 images to 39204 images. The tuned model achieves 97% accuracy for the augmented dataset.

III. METHODOLOGY

The proposed work utilizes deep CNN with eight layers to characterise various diseases in tomato, apple, peach, and maize leaves. Fig 1 displays the workflow of the proposed model.

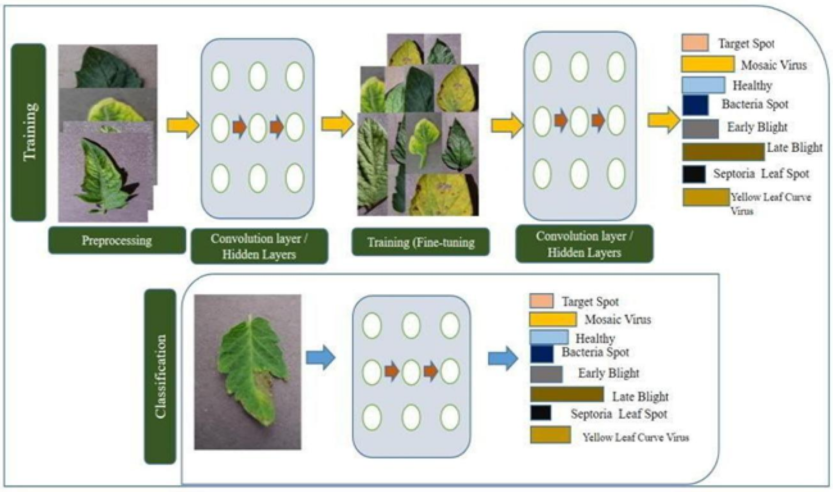

Figure 1 :Flow diagram of MCC-ECNN model

The MCC-ECNN has three main stages:

Pre-processing

This step involves the selection of the dataset. Manually, the datasets are separated based on the stages of the diseases. The diseases are divided into three stages: early, mild, and severe.One of the most vital elements of any deep learning application is to train the dataset using the model. In the proposed work, images are taken from the plant village dataset. It consists of 13257 images of tomato leaves, 3150 images.of maize leaves, 1056 images of peach leaves, and 2183 images of apple leaves, including both healthy and non-healthy leaves. The dataset is initially divided into a ratio of 80:20 or 70:30 for the training phase and the test phase to improve the results. The accuracy of the network depends on the size and proportion of the date taken for training and testing. Overfitting of data results in high test dataset errors, and underfitting leads to both high training and test errors. In the proposed method, the dataset is divided into 80:20. All the images are resized to 256 x 256 as a pre-processing step to reduce the time complexity of the training phase.

MCC-ECNN Model

The MCC-ECNN model consists of eight layers, including the convolutional layers, pooling layers, dense layers, and flattens layers. The most critical layer of Deep CNN is the convolution layer; the main working process of this layer is to extract the feature information from the input images. In the first convolution layer, 224 x 224 x 3 (width x height x color) as the dimensioned input images are given. The filter size of this layer is 32 x 3 x 3, and the activation function is ReLU. The output of the first layer is 224 x 224 x 3 after generating the convolution function.

The output of the first convolution layer was given as an input to the pooling layer. It performs the down-sampling operation along with the spatial dimensions and reduces the number of parameters. The max pooling was used in the proposed MCC-ECNN model and it achieves better performance when For image identification and classification applications, CNNs are frequently utilised. For illustration, CNN's[16].

compared with min pooling and average pooling. Batch normalization helps to learn faster and achieve higher overall accuracy. Both the ReLU activation function and batch normalization are applied in all experiments. One important feature of ReLU is that it eliminates negative values in the given input by replacing them with zero. This model uses

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, July 2024

binary cross-entropy rather than categorical cross-entropy. Dropout is a technique that is used to reduce overfitting in the model during the training set. The softmax function is used in the final layer of the deep learning-based classifier. The complete layered architecture of the MCC-ECNN model was shown in Fig. 2

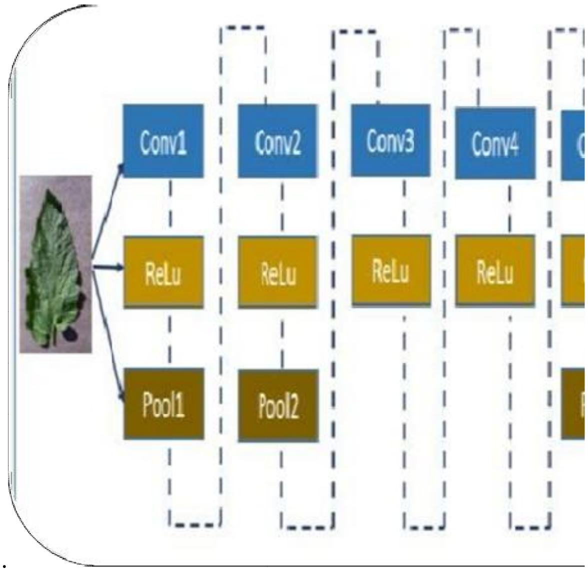

Fig 2: Architecture of MCC- ECNN Architecture

Model Testing

In this phase, the validation dataset is utilized to estimate the classifier's performance. Fine-tuning helps to improve the accuracy of classification by making small modifications in hyper-parameters and by increasing the number of layers and batch size. The algorithmic steps of MCC-ECNN are summarized in Algorithm.

Algorithm: MCC-ECNN Net Architecture
Input: Plant village Dataset
Output: Classification of plant leaf disease
Begin
Phase 1: Preprocessing
1. Read the dataset
2. Pre-process the data
Divide the stages of diseases Resize the image
3. Splitting the dataset with the appropriate proportion for training and testing
Phase 2: Train the Model
4. Train the MCC-ECNN model
5. Tune the hyper parameters
• Batch Size
• Number of images
Phase 3: Test the Model
6. Test the MCC-ECNN model with the test dataset
7. Classify the disease.
End

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 2, July 2024

IV. RESULT AND DISCUSSION

The experimental results of our MCC-ECNN model for the plant village dataset are shown in Table 1. It lists the classification accuracy of each of the twenty diseases and healthy leaves. The dataset contains more than 1000 images under each disease class with a maximum limit of 1246 images.

Table 1: Classification Accuracy of Various Tomato Leaf Diseases using MCC-ECNN model

No. of Images	Bacterial Spot	Early Blight	Late Blight	Septoria Spot	Target Spot	Yellow Curl virus	Mosaic virus
400	72.49	68.24	63.29	60.35	40.86	78.97	61
728	84.86	91.59	82.29	75.86	80.75	96.76	91.4
953	90.26	94.86	93.12	85.45	91.5	85.82	78.65
1246	99.94	98.69	98.71	98.46	98.4	99.91	99.74

The graphical demonstration of the accuracy of the model is depicted in Fig 3

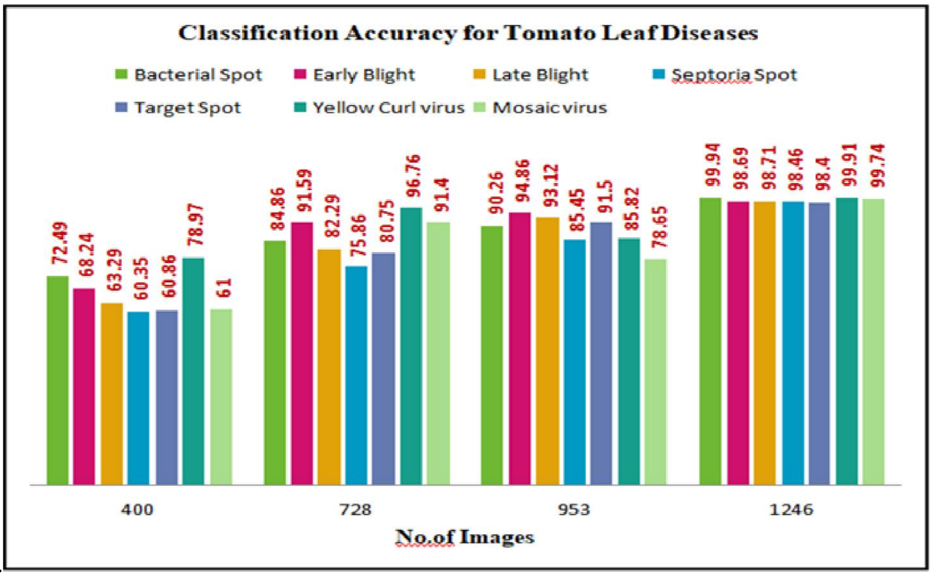

Fig. 3: The classification accuracy for Tomato leaf using MCC- ECNN Model

Table 4.2 presents the influence of the classification accuracy of various images. It is obvious from Table 3.3 that accuracy increases with increase in the number of images of maize leaves. For larger dataset, the accuracy has increased up to 96.45%.

Table 2: Classification Accuracy of Various Maize Leaf Diseases using MCC-ECNN Model

No. of Images	Northern Leaf Blight	Brown Spot	Round Spot
200	62.94	68.24	63.29
400	74.52	78.23	76.12
600	83.75	84.91	83.08
850	95.17	96.45	94.65

The graphical illustration of the accuracy of the model is depicted in Fig 4.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, July 2024

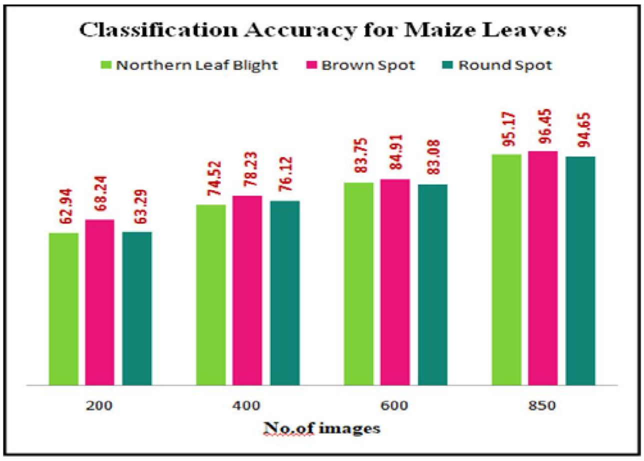

Fig. 4: The Classification Accuracy for Maize Leaf using MCC- ECNN Model

Table 3 presents the influence of batch size on classification accuracy. It is obvious from Table 3 that accuracy increases with minibatch size. It is also worth noting that there is not much increase in accuracy for batch sizes 16, 32 and 64. There is a steep rise in accuracy from batch size 2 to 8.

Table 3: Classification Accuracy for Various Batch Sizes for Tomato Leaves.

Batch size	Bacterial Spot	Early Blight	Late Blight	Septoria Spot	Target Spot	Yellow curl virus	Mosaic virus
2	72.49	68.24	63.29	68.11	73.58	69.95	81
8	91.97	70.14	93.1	93.78	88.48	97.82	98.21
16	95.39	97.55	94.57	95.95	91.91	98.84	98.91
32	98.7	98.41	97.96	98.16	95.8	99.5	98.24
64	99.05	99	98.25	98.73	98.78	99.12	99.74

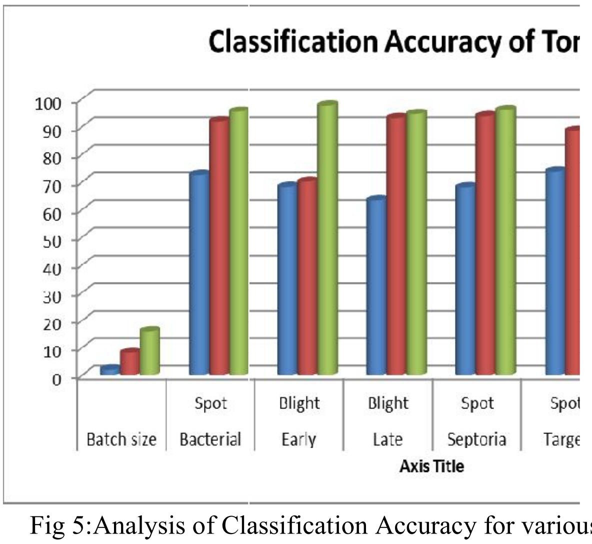

Fig 5:Analysis of Classification Accuracy for various batch sizes (Tomato Leaves)

Table 3 presents the influence of batch size on the classification accuracy of maize leaves. Table 3 demonstrates that accuracy increases with minibatch size. It is also worth noting that there is not much increase in accuracy for batch sizes 32 and 64 for Brown spot and Round spot leaf images.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 2, July 2024

Table 4: Classification Accuracy for Various Batch Sizes for Maize Leaves

Batch size	Northern Leaf Blight	Brown Spot	Round Spot
2	69.27	67.87	65.45
8	89.62	70.53	87.76
16	90.46	92.47	90.35
32	93.65	94.01	93.43
64	95.31	94.56	94.86

The graphical representation of Table 4 is presented in Fig 6

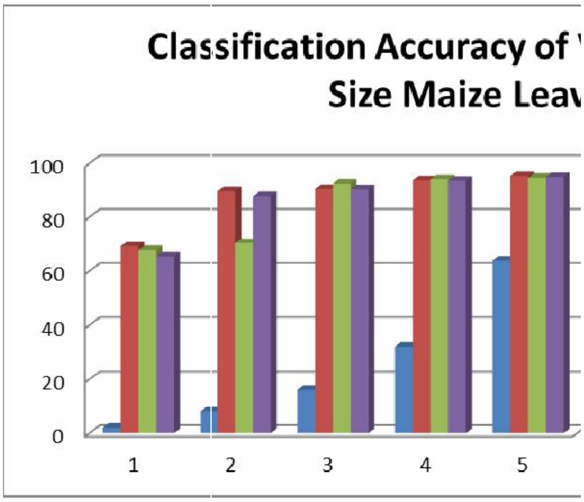

Fig 6: Analysis of Classification Accuracy for various batch sizes (Maize Leaves)

Table 4 presents the influence of batch size on the classification accuracy of apple and peach leaves. Table 4 demonstrates that accuracy increases with minibatch size. It is also worth noting that higher accuracy is achieved for batch size 64.

V. CONCLUSION

Using a plant village dataset, an MCC-ECNN model was used to classify diseases affecting tomato, maize, apple and peach leaves using in this study. The model uses five layers to create the model to classify the disease. The model achieved 99.18% for tomato leaves, 84.41% for apple leave, 87.12% for peach leaves, and 94.91% for maize leaves, according to the results. Classification accuracy is evaluated with 20,877 images of healthy and unhealthy tomato, apple, peach, and maize leaves..

REFERENCES

[1]. Agarwal, M., Bohat, V. K., Ansari, M. D., Sinha, A., Gupta, S. K., &Garg, D. (2019, December). A convolution neural network based approach to detect the disease in corn crop. In 2019 IEEE 9th international conference on advanced computing (IACC) (pp. 176-181). IEEE.

[2]. Agarwal, M., Gupta, S. K., &Biswas, K. K. (2019, October). Grape disease identification using convolution neural network. In 2019 23rd International Computer Science and Engineering Conference (ICSEC) (pp. 224-229). IEEE.

[3]. Agarwal, M., Gupta, S., &Biswas, K. K. (2021). A new Conv2D model with modified ReLU activation function for identification of disease type and severity in cucumber plant. Sustainable Computing: Informatics and Systems, 30, 100473.

[4]. Agarwal, M., Singh, A., Arjaria, S., Sinha, A., & Gupta, S. (2020). ToLeD: Tomato leaf disease detection using convolution neural network. Procedia Computer Science, 167, 293-301.

[5]. Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., ...&Asari, V. K. (2019). A state-of-the-art survey on deep learning theory and architectures. Electronics, 8(3), 292.

[6]. Amara, J., Bouaziz, B., &Algergawy, A. (2017). A deep learning-based approach for banana leaf diseases classification. Datenbanksystemefür Business, Technologie und Web (BTW 2017)-Workshopband.

[7]. ArnalBarbedo, J. G. A. (2019). Plant disease identification from individual lesions and spots using deep learning. Biosystems Engineering, 180, 96-107.

[8]. Attallah, O., 2023. Tomato Leaf Disease Classification via Compact Convolutional Neural Networks with Transfer Learning and Feature Selection. Horticulturae, 9(2), p.149.

[9]. Binnar, V. and Sharma, S., 2023, January. Plant Leaf Diseases Detection Using Deep Learning Algorithms. In Machine Learning, Image Processing, Network Security and Data Sciences: Select Proceedings of 3rd International Conference on MIND 2021 (pp. 217-228). Singapore: Springer Nature Singapore.

[10]. Cheng, X., Zhang, Y., Chen, Y., Wu, Y., &Yue, Y. (2017). Pest identification via deep residual learning in complex background. Computers and Electronics in Agriculture, 141, 351-356.

[11]. DeChant, C., Wiesner-Hanks, T., Chen, S., Stewart, E. L., Yosinski, J., Gore, M. A.,& Lipson, H. (2017). Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning. Phytopathology, 107(11), 1426- 1432.

[12]. Deshpande, R. and Patidar, H., 2023. Tomato plant leaf disease detection using generative adversarial network and deep convolutional neural network. The Imaging Science Journal, pp.1-9.

[13]. Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and electronics in agriculture, 145, 311-318.

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

[15]. Geetharamani, G., &Pandian, A. (2019). Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computers & Electrical Engineering, 76, 323-338.

[16]. Geetharamani, G., &Pandian, A. (2019). Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computers & Electrical Engineering, 76, 323-338.

[17]. Gonzalez, R. C., Woods, R. E., &Eddins, S. L. (2010). Morphological reconstruction. Digital image processing using MATLAB, MathWorks.

[18]. Guerrero-Ibañez, A. and Reyes-Muñoz, A., 2023. Monitoring Tomato Leaf Disease through Convolutional Neural Networks. Electronics, 12(1), p.229.

[19]. Gupta, S., Sangeeta, R., Mishra, R. S., Singal, G., Badal, T., &Garg, D. (2020). Corridor segmentation for automatic robot navigation in indoor environment using edge devices. Computer Networks, 178, 107374.

[20]. Hari, S. S., Sivakumar, M., Renuga, P., &Suriya, S. (2019, March). Detection of plant disease by leaf image using convolutional neural network. In 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN) (pp. 1-5). IEEE.

[21]. Hasan, M., Tanawala, B., & Patel, K. J. (2019, March). Deep learning precision farming: Tomato leaf disease detection by transfer learning. In Proceedings of 2nd international conference on advanced computing and software engineering (ICACSE).

[22]. Hu, R., Zhang, S., Wang, P., Xu, G., Wang, D., &Qian, Y. (2020, May). The identification of corn leaf diseases based on transfer learning and data augmentation. In proceedings of the 2020 3rd international conference on computer science and software engineering (pp. 58-65).

[23]. Karthikeyan, N., & Rani, M. S. (2022). ECG Classification Using Machine Learning Classifiers with Optimal Feature Selection Methods. In Evolutionary Computing and Mobile Sustainable Networks (pp. 277-289). Springer, Singapore.

[24]. Kaushik, M., Prakash, P., Ajay, R., &Veni, S. (2020, June). Tomato leaf disease detection using convolutional neural network with data augmentation. In 2020 5th International Conference on Communication and Electronics Systems (ICCES) (pp. 1125-1132). IEEE.

[25]. Kawasaki, Y., Uga, H., Kagiwada, S., &Iyatomi, H. (2015, December). Basic study of automated diagnosis of viral plant diseases using convolutional neural networks. In International symposium on visual computing (pp. 638-645). Springer, Cham.

[26]. Kubat, M., &Kubat. (2017). An introduction to machine learning (Vol. 2). Cham, Switzerland: Springer International Publishing.

[27]. Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267, 378-384.

[28]. Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267, 378-384.

[29]. Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. Computers and electronics in agriculture, 154, 18-24.

[30]. Mary Shanthi Rani, M., Chitra, P., Lakshmanan, S., Kalpana Devi, M., Sangeetha, R., &Nithya, S. (2022). DeepCompNet: A Novel Neural Net Model Compression Architecture. Computational Intelligence and Neuroscience, 2022.

[31]. Mohanty, S. P., Hughes, D. P., &Salathé, M. (2016). Using deep learning for image- based plant disease detection. Frontiers in plant science, 7, 1419.

[32]. Nachtigall, L. G., Araujo, R. M., &Nachtigall, G. R. (2016, November). Classification of apple tree disorders using convolutional neural networks. In 2016 IEEE 28th International Conference on Tools with Artificial Intelligence (ICTAI) (pp. 472- 476). IEEE.

[33]. Nawaz, M., Nazir, T., Javed, A., Masood, M., Rashid, J., Kim, J. and Hussain, A., 2022. A robust deep learning approach for tomato plant leaf disease localization and classification. Scientific Reports, 12(1), p.18568.

[34]. Negi, A., Kumar, K. and Chauhan, P., 2021. Deep neural network-based multi-class image classification for plant diseases. Agricultural informatics: automation using the IoT and machine learning, pp.117-129.

[35]. Oppenheim, D., &Shani, G. (2017). Potato disease classification using convolution neural networks. Advances in Animal Biosciences, 8(2), 244-249.

[36]. Pandian, J. A., Geetharamani, G., & Annette, B. (2019, December). Data augmentation on plant leaf disease image dataset using image manipulation and deep learning techniques. In 2019 IEEE 9th international conference on advanced computing (IACC) (pp. 199-204). IEEE.

[37]. Rangarajan, A. K., Purushothaman, R., & Ramesh, A. (2018). Tomato crop disease classification using pre-trained deep learning algorithm. Procedia computer science, 133, 1040-1047.

[38]. Roy, A.M. and Bhaduri, J., 2021. A deep learning enabled multi-class plant disease detection model based on computer vision. Ai, 2(3), pp.413-428.

[39]. Roy, K., Chaudhuri, S.S., Frnda, J., Bandopadhyay, S., Ray, I.J., Banerjee, S. and Nedoma, J., 2023. Detection of Tomato Leaf Diseases for Agro-Based Industries using novel PCA DeepNet. IEEE Access.

[40]. Sa, I., Ge, Z., Dayoub, F., Upcroft, B., Perez, T., & McCool, C. (2016). Deepfruits: A fruit detection system using deep neural networks. sensors, 16(8), 1222.

[41]. Sabrol, H., & Kumar, S. (2016). Fuzzy and neural network based tomato plant disease classification using natural outdoor images. Indian J. Sci. Technol, 9(44), 1-8.

[42]. Saeed, A., Abdel-Aziz, A.A., Mossad, A., Abdelhamid, M.A., Alkhaled, A.Y. and Mayhoub, M., 2023. Smart Detection of Tomato Leaf Diseases Using Transfer Learning-Based Convolutional Neural Networks. Agriculture, 13(1), p.139.

[43]. Sangeetha, R., & Mary Shanthi Rani, M. (2021). A novel method for plant leaf disease classification using deep learning techniques. In Machine Learning, Deep Learning and Computational Intelligence for Wireless Communication (pp. 631- 643). Springer, Singapore.

[44]. Sangeetha, R., & Rani, M. (2020, December). Tomato leaf disease prediction using transfer learning. In International Advanced Computing Conference (pp. 3-18). Springer, Singapore.

[45]. Sangeetha, R., & Rani, M. M. S. (2019). Tomato leaf disease prediction using convolutional neural network. Int. J. Innov. Technol. Explor. Eng, 9(1), 1348- 1352.

[46]. Sangeetha, R., & Rani, M. M. S. (2019). Tomato leaf disease prediction using convolutional neural network. Int. J. Innov. Technol. Explor. Eng, 9(1), 1348- 1352.

[47]. Sangeetha, R., Mary Shanthi Rani, M., & Joseph, R. (2021, December). Optimized Deep Neural Network for Tomato Leaf Diseases Identification. In International Advanced Computing Conference (pp. 562-576). Springer, Cham.

[48]. Sharma, A., Sharma, K., & Kumar, A. (2022). Real-time emotional health detection using fine-tuned transfer networks with multimodal fusion. Neural Computing and Applications, 1-14.

[49]. 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.

[50]. Sonka, M., Hlavac, V., & Boyle, R. (2014). Image processing, analysis, and machine vision. Cengage Learning.

[51]. Srivastava, S., Boyat, S., &Sadistap, S. (2014). A novel vision sensing system for tomato quality detection. International journal of food science, 2014.

[52]. Uğuz, S., &Uysal, N. (2021). Classification of olive leaf diseases using deep convolutional neural networks. Neural Computing and Applications, 33(9), 4133- 4149.

[53]. Wu, Q., Chen, Y., &Meng, J. (2020). DCGAN-based data augmentation for tomato leaf disease identification. IEEE Access, 8, 98716-98728.

[54]. Yulita, I.N., Amri, N.A. and Hidayat, A., 2023. Mobile Application for Tomato Plant Leaf Disease Detection Using a Dense Convolutional Network Architecture. Computation, 11(2), p.20.

[55]. Zhang, K., Wu, Q., Liu, A., &Meng, X. (2018). Can deep learning identify tomato leaf disease?.Advances in multimedia, 2018.

[56]. Zhu, X., Liu, Y., Li, J., Wan, T., & Qin, Z. (2018, June). Emotion classification with data augmentation using generative adversarial networks. In Pacific-Asia conference on knowledge discovery and data mining (pp. 349-360). Springer, Cham.